Faculty of Business Studies and Economics
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Doctoral Thesis

Green Technologies and Their Role for Sustainability

Essays on Environmental Innovation

A thesis submitted to the Doctoral Commission Dr. rer. pol. of the University of Bremen in fulfilment of the requirements for the degree of Dr. rer. pol.

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Chapter 1

Introduction: on Technology and Sustainability

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Abstract

This introduction takes a holistic perspective on the empirical studies to follow (chapters 2 to 5), emphasizing the crucial importance of technology in human development and its pivotal role for the future of humanity. First, the sustainability problem (section 2) is discussed. Human dependence on the environment, insights from the natural sciences concerning the interrelation of humans with their environment, the driving forces behind and magnitude of pressure humans put on the environment, and the fundamental debate over economic growth are covered in this section. Section 3 takes a look at technology from several perspectives. Fundamental characteristics of technology and technological change, the historical role of technology in human development, and the interrelation between technology and the environment are examined. Section 4 presents an overview of the dissertation, including a clarification of the concept of environmental innovation (EI) and a summary of the empirical studies that make up the body of the dissertation. The intrusive conclusion (section 5) is twofold. First, technology alone will not solve the environmental problems facing humanity. Second, a fundamental shift of the role played by technology is indispensable.

Keywords: Decoupling ® Environmental Innovation ® Green Technological Change ® Planetary Boundaries ® Sustainable Development

JEL Classification: O13; O33; O44; Q00; Q01; Q55

Publication

This is the introductory paper of this cumulative thesis submitted to the Doctoral Commission of Bremen in fulfilment of the requirements for a Dr. rer. pol. degree.

1.1 Introduction

When first introduced around 1700, the term ‘sustainability’ referred to forestry and meant that in order to preserve the forest one can harvest only as much wood from the forest as the forest can grow (Fischler, 2014). Broader attention was devoted to the term when the seminal report *The Limits to growth* (Meadows et al., 1972) was published in 1972, and sparked a debate on the durability of global human development. The concept of sustainability is at its core concerned with future viability (Fischler, 2014). Since the onset of the Industrial Revolution around 1800 humanity has constantly increased its economic activities at the cost of increasing resource consumption and waste production (Malm, 2013; Steffen et al., 2007; UNEP, 2016). These impacts on the natural environment have surpassed the sustainable level, such that humanity is threatening the natural environment on which it depends (Schramski et al., 2015). Aligning the preservation of a functional natural environment with human needs has become an overarching goal on the global political agenda (United Nations, 2015).

Technological progress is often considered to be a panacea for solving the conflicting human desires of economic activity and environmental quality (Asafu-Adjaye et al., 2015; Fücks, 2013). In this context, innovation is demanded to improve the technological landscape. More specifically, technologies that explicitly foster the preservation of environmental quality are pursued (Aghion et al., 2009), in order to allow continued economic growth while sparing the environment. Such technologies have been conceptualized as a subset of technologies with specific characteristics (Kemp and Pearson, 2007; Rennings, 2000), and are considered to be of pivotal importance for achieving sustainability (Aghion et al., 2009; European Commission, 2011; Hepburn et al., 2018; Popp et al., 2010). The present thesis is fundamentally concerned with this concept, known as ‘environmental innovation’ (EI) (Barbieri et al., 2016).

The present thesis includes this introductory chapter and four scientific articles (chapters 2 - 5). The scientific articles contribute to understanding the determinants of EI, which is of importance due to the specific characteristics of EI (Rennings, 2000), and the assessment of the environmental effects of EI, which is of even greater importance because of the hope attached to green technologies. Chapter 2 investigates the role of institutional factors in the introduction of EI by European firms. In chapter 3, the effects of EI on carbon dioxide emissions in European countries are analysed. Chapter 4 is dedicated to establishing and testing the linkage between EI and resource use, and chapter 5 analyses the extent to which EI has reduced the utilization of biomass and fossil resources.

This introductory chapter will provide the foundation for embedding the subsequent chapters in the larger context of EI. Section 2 will introduce the concept and issue of sustainability. This includes establishing the interrelation of humans with their natural environment (2.1) and introducing the laws and dynamics by which this interrelation is governed (2.2). Being compounded by human influences, the determinants of environmental pressure are introduced and discussed, along with empirical evidence on the magnitude of environmental pressures exerted by humans (2.3). The ‘growth debate’ is central to any discussion of sustainability issues, and will be introduced in section 2.4. Section 3 is devoted to presenting the concept of technology and technological development in a holistic manner. To this purpose, some fundamental characteristics of technology and technological change are introduced (3.1). This is followed by introducing a historical dimension to contextualize the long-term dynamics of technological development, human development, and the environmental consequences (3.2). The dynamics of technology are discussed in section 3.3, with a special focus on the interrelation of technology with environmental issues, and the prospects of technology alleviating environmental issues in the future. Section 4 offers an in-depth examination of the concept of EI, and its specific place in the other chapters of this thesis. After the concept and definition of EI are discussed, there is a brief overview of the extant literature, its typologies and methods of measurement (4.1). Section 4.2 gives a detailed introduction to the scientific articles (chapters 2 - 5). Section 5 synthesises the main findings within holistic considerations, draws conclusions, and gives an outlook on future challenges.

1.2 The Sustainability Problem

In 1972, the seminal *The Limits to Growth* (LtG) report by the Club of Rome suggested that the current global system is heading toward an environment-based collapse (Meadows et al., 1972). With a focus on system dynamics of interrelated economic subsystems, namely population, food production, industrial production, pollution, and consumption of non-renewable natural resources, the scenarios showed that a shift in the fundamental pattern is required to avoid collapse within the next ~ 100 years (Meadows et al., 1972). *The Limits to Growth* constitutes a pioneering scientific work on the dangers of a globally growing economy. Politically, the agenda for sustainability was set 15 years later with the so-called *Brundtland Report*. It defined the concept of sustainable development as *“... development that meets the needs of the present* *without compromising the ability of future generations to meet their own needs*" (World Commission on Environment and Development, 1987, p. 43).[1]

The term 'sustainable development' has become the superordinate notion in the pursuit of aligning societal (social and economic) development with ecological restrictions. At its core, the definition of Sustainable Development, as introduced by the *Brundtland Report*, did not preclude further economic growth; on the contrary a new era of economic growth was envisaged (World Commission on Environment and Development, 1987). Hence, the term of Sustainable Development aligned the socio-political desire for continued economic growth (Schmelzer, 2015) with the ecological concerns raised by the LtG report (Meadows et al., 1972). This hope for the alignment of economic growth and environmental quality is more recently reflected in the United Nations Sustainable Development Goals (United Nations, 2015).

In the present thesis, central importance is assigned to the sustainability issue due to four principal realities. First, because humans are dependent on their natural environment in order to operate as a society, some characteristics of this dependence will be discussed. Second, because the natural environment is governed by incontrovertible laws and dynamics, some basic environmental science will be introduced to set the scene for the scope and limits to human activity on planet Earth. Third, because humans have become capable of significantly influencing the global environment, the determinants of human-induced environmental stress will be introduced, along with an exploration of the magnitude these human influences have taken on over time. Fourth, because the effects humans exert on the environment depend on certain components that are interconnected and subject to change due to human action, the debate on economic growth as the driving force of ecological deterioration will be discussed with a focus on social desirability, ecological feasibility, and socio-economic necessity. In this way, section 2 clarifies the relevance of the topic, and outlines the main aspects to be taken into consideration.

[1] A more extensive, yet less well-known, definition was given as: "In essence, sustainable development is a process of change in which the exploitation of resources, the direction of investments, the orientation of technological development, and institutional change are all in harmony and enhance both current and future potential to meet human needs and aspirations" (World Commission on Environment and Development, 1987, p. 46).

1.2.1 Interactions of the Environment and the Economy

Economic activity is embedded in the natural environment. The economy can be considered to be a subsystem of a larger ecosystem, namely the earth system (Daly, 1987; Steffen et al., 2007). The earth system is a thermodynamically closed system. In other words, while energy enters the system in the form of solar radiation, matter is not exchanged with the outside (Perman et al., 2011; Schramski et al., 2015).

Like all other living beings in the earth system, humans rely on natural resources for their survival and to fulfil their needs. The resources provided by the natural environment can broadly be categorized as flow and stock resources. The future availability of flow resources is not dependent on current use (Perman et al., 2011). Solar radiation, for example, enters the earth system regardless of whether it is used for heating or photosynthesis. The future availability of stock resources, on the other hand, is characterized by being dependent on current use (Perman et al., 2011). Stock resources are divided into renewable and non-renewable resources (Perman et al., 2011). Biomass qualifies as a renewable resource because it is possible to reproduce it in a timely manner. In other words, it is a resource that can be used indefinitely if usage does not exceed replenishment. Minerals are considered to be non-renewable resources because replenishment only occurs in geological timescales. Hence, in the case of minerals (including fossil fuels) there is a finite supply and any consumption reduces the available stock size.

Perman et al. (2011) consider four main categories of environmental services that humans rely upon from the biosphere. First, the environment serves as a resource base. As noted above, the resources that are drawn upon can differ in characteristics, with important implications for the sustainability of an economy. For example, the combustion of fossil fuels is inherently dissipative (Ayres, 1989), whereas minerals used for the production of a good are available for recycling (Perman et al., 2011). Second, the environment serves as a waste sink as residuals from economic activity are discharged into the environment. According to the materials-balance principle, which will be explained later, the mass of these residuals will eventually be identical to the resources initially extracted (Ayres, 1989). The role of wastes is crucial due to the implications for the functioning of an ecosystem. Third, the environment provides amenity services. For example, without any productive activity the presence of a beautiful landscape is of value to humans. Fourth, the environment provides basic life-support functions. For example, the natural greenhouse effect enables an environment that is beneficial for the formation and preservation of human life (Boyes and Stanisstreet, 1993).

A fundamental question as to the degree of human dependence on the environment concerns the capability of substituting environmental services. Substitution of some portion of environmental services with man-made capital and technology is definitely possible. There are many clarifying examples of this when considering the environment as a resource base or waste sink: Improvements in recycling reduce the amount of virgin raw materials that need to be extracted from the environment; a sewage treatment plant can reduce the pressure on the absorbing ecosystem. However, if we consider the context of the life-support functions of the environment, it seems difficult to substitute these services on a whole earth system´s scale (Perman et al., 2011). These considerations have been contextualized by the term ‘natural capital’, and refers to the continued and future provision and flow of valuable goods and services originating from the environment to humans (Costanza and Daly, 1992). This resulted in a distinction between ‘weak’ and ‘strong’ sustainability. The concept of weak sustainability assumes a perfect substitutability between natural and man-made capital (Weisz et al., 2006). Strong sustainability, on the contrary, distinguishes between man-made and natural capital (Pelenc and Ballet, 2015). Natural capital is characterized as showing phenomena of irreversibility and thresholds, and is essential to producing manufactured capital in the first place (Pelenc and Ballet, 2015). Furthermore, natural capital is multifunctional, uncertainty about the effects of natural capital reduction exists, and loss of natural capital imposes restrictions on the decisions future generations can make (Pelenc and Ballet, 2015). In essence, the strong sustainability approach considers substitutability of natural capital to be limited, as some ‘critical natural capital’ (Ekins et al., 2003) cannot be substituted. However, debates on this issue strongly depend on certain questions of environmental science that will now be explored in more depth.

1.2.2 Insights From Environmental Science

In order to understand and evaluate human activity in the context of environmental issues, it is essential to be aware of the mechanisms by which the environment/economy relationship is governed. Therefore, some fundamental concepts and principles of environmental science will be introduced. This encompasses the implications of thermodynamics for economic activity, and concepts from ecology that are relevant to conceptualize the impacts of human activity and the systemic character of the environment.

1.2.2.1 Important Aspects of Thermodynamics

The laws of thermodynamics are incontrovertible (Schramski et al., 2015). The relevance of thermodynamics to economics was pointed out in the context that standard economic theory implicitly treats the economic system as circular and self-sustaining (Georgescu-Roegen, 1971). Thermodynamics is concerned with the science of energy, whereby energy is a characteristic of how far a property is from equilibrium (Perman et al., 2011; Schramski et al., 2015). This ‘gradient’ (Schramski et al., 2015) can be used to perform work or supply heat (Perman et al., 2011; Schramski et al., 2015). Work is required to fuel the complex socio-economic activities humans engage in (Schramski et al., 2015). The first and second law of thermodynamics will be introduced and discussed concerning their implications.

The first law of thermodynamics stipulates that energy can neither be created nor destroyed (Mayumi, 2017; Perman et al., 2011; Schramski et al., 2015). While it changes forms during transformations between solar, chemical, work, and heat, the total quantity in an isolated system is conserved (Mayumi, 2017; Schramski et al., 2015).[2] In a societal context it follows that energy neither is *“... consumed nor produced in economic processes”* (Kåberger and Månsson, 2001, p. 166). The materials-balance principle, as an application of the first law (Ayres, 1989), refers to the law of conservation of mass that matter can neither be created nor destroyed (Perman et al., 2011).

The second law of thermodynamics, known as the ‘entropy law’ (Perman et al., 2011), is considered to be the root cause of economic scarcity (Georgescu-Roegen, 1979). This law states that heat flows spontaneously from a hotter to a colder body, and that heat cannot be converted completely into work (Mayumi, 2017; Perman et al., 2011). The law of entropy also states that as energy changes forms, all energy is eventually degraded to low-quality heat energy (Schramski et al., 2015). In the societal context it can be formulated that *“every economic process results in an increase in total entropy”* (Kåberger and Månsson, 2001, p. 166). Entropy itself is a measure of how dispersed energy is (Mayumi, 2017), i.e., unavailable energy (Perman et al., 2011).

Thermodynamics capture the biophysical dimension of energy and material transformation in the economic process. The materials-balance principle implies that since the economic process cannot create matter, economic activity involves transforming matter extracted from the environment into some material good (Perman et al., 2011). Further, this implies that all of the

[2] An isolated system exchanges neither matter nor energy across its system boundary (Mayumi, 2017).

extracted matter will eventually be returned to the environment in a transformed state, leading to issues concerning residual discharge (Ayres and Kneese, 1969). Mayumi (2017) concludes two implications from the first law. First, the only stocks of natural resources are those in existence as matter-energy cannot be created, leading to implications of stock exhaustion for economic processes that are reliant upon specific characteristics of the material involved. Second, what has been produced cannot be removed, which leads to unwanted waste flows finally residing in the environment.

The second law of thermodynamics has crucially important implications for economic processes (Georgescu-Roegen, 1971). Energy stores have varying shares of energy available for conversion, as all conversions of energy are less than 100% efficient (Perman et al., 2011). This leads to the irreversibility of real processes as available energy can only be used once (Mayumi, 2017). In other words, in an isolated system the energy available in a transformed state is insufficient to restore the original state (Perman et al., 2011). The second law also implies that energy efficiency can never surpass the thermodynamic maximum, i.e., there is a set limit to the efficiency of a system (Mayumi, 2017). The limited availability of energy is softened by incoming solar radiation that is a source of energy being added to the system (Mayumi, 2017). Nevertheless, because material transformations involve work, they require energy. This implies that, in the absence of an abundant stock energy source, the incoming solar energy constitutes the upper limit on the amount of work that can be carried out (Perman et al., 2011). Complete material recycling remains practically impossible (Bianciardi et al., 1993; Cullen, 2017).

The laws of thermodynamics facilitate a better understanding of the core issues for sustainability. First, economic activity depends on energy, and the amount of available energy is effectively limited (Mayumi, 2017; Perman et al., 2011). Second, physical resources of low entropy are crucial for managing processes desired by humans (Kåberger and Månsson, 2001), and these are consequently also limited (Schramski et al., 2015). Third, the use of resources proportionally implies wastes to be discarded into the environment (Ayres and Kneese, 1969). The implications of these aspects for economic activity will be discussed in more detail later, with respect to energy consumption levels and the prospects for recycling and a circular economy.

Finally, it should be noted that the generic nature of thermodynamics limits the applicability to complex socio-economic systems (Mayumi, 2017). For example, although the mass of residuals may remain the same, the location to which residuals are disposed or their form have implications for the environmental problems arising from waste disposal (Perman et al., 2011). Thus, while the application of entropy to economic contexts should be treated with caution, the implications of incontrovertible limits are of crucial importance for the sustainability issue. Hence, the next section will serve to discuss some principles from ecology, which are relevant as we are embedded in, and dependent upon, ecosystems and their services.

1.2.2.2 Important Aspects of Ecology

As noted before, humans are dependent on a wide array of services and resources stemming from the environment. Even fundamental life-support functions, such as oxygen production, are provided by ecosystems. An ecosystem is *"... a dynamic complex of plants, animals, microbes, and physical environmental features that interact with one another"* (Millennium Ecosystem Assessment, 2005, p. 3). Different types of ecosystems deliver different types of ecosystem services. Ecosystem services can be characterized as *"... the benefits that humans obtain from ecosystems..."* (Millennium Ecosystem Assessment, 2005, p. 3). These services are provided by interactions within the ecosystem. They have been categorized as provisioning, regulating, cultural, and supporting services. Cultural services include aesthetic or spiritual services. Regulating services include climate or flood regulation. Provisioning services include food or fuel provision. Lastly, supporting services include nutrient cycling and soil formation. These basic services are needed to maintain the other categories of services (Millennium Ecosystem Assessment, 2005).[3] Ecosystem services vary concerning their regional significance, ranging from local services, such as provision of pollinators, to global services, such as climate regulation (Millennium Ecosystem Assessment, 2005). Consequently, the environmental services needed by humans are dependent upon dynamic and complex systems, with the potential of disturbances causing severe changes in their provision (Millennium Ecosystem Assessment, 2005). The impact of human activity on ecosystems is highly relevant when considering environmental pressure and sustainability issues. Because these considerations go hand in hand with concerns about energy and resource limits,[4] we must discuss the fundamental concepts of stability and resilience with a particular focus on biodiversity.

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[3] Note that these ecosystem services correspond to the environmental services humans depend upon according to Perman et al. (2011).

[4] As Boulding (1966, p. 11) states: *„Oddly enough, it seems to be in pollution rather than in exhaustion that the problem is first becoming salient."*

Holling (1973) proposed the concepts of stability and resilience as a way to define and describe the behaviour of ecological systems. Stability is the ability of a system to return to an equilibrium state after it has been subjected to a disturbance. Systems that have a low level of fluctuation and a higher speed of adjustment have a higher level of stability (Holling, 1973). The concept of resilience describes *"... the capacity of a system to absorb disturbance and reorganize while undergoing change so as to still retain essentially the same function, structure, identity, and feedbacks"* (Walker et al., 2004, p. 2). Crucial aspects of resilience include the concepts of latitude and precariousness (Walker et al., 2004). Latitude defines the degree to which a system can be changed before it loses its ability to recover by crossing a threshold (Walker et al., 2004). Crossing a threshold value marks a sudden change in feedbacks within an ecosystem (Folke et al., 2004). Precariousness captures how close the system currently is to such threshold (Walker et al., 2004). Economic activity can adversely influence the resilience of ecosystems. This can take the shape of reductions of latitude, i.e., increases of precariousness, as safety margins towards critical thresholds are reduced (Perman et al., 2011). Yet, dose-response relationships, which refer to the response of the system for instance to levels of pollution, include non-linearities and thresholds (Perman et al., 2011). Such thresholds are considered to be "tipping points" in the context of climate change, for example, implying fundamental changes caused by crossing a certain boundary (Rockström et al., 2009). Disturbances to an ecosystem of a sufficient magnitude and duration can cause a regime shift that has implications for the services an ecosystem is able to provide (Folke et al., 2004). Adverse effects of human activities can cause regime shifts that have negative consequences on the capacity of ecosystems to support human purposes (Folke et al., 2004). These regime shifts can not only decrease the internal resilience of a specific system, but also create external disturbances that impact other systems as well (Folke et al., 2004). In this way, the dynamics of biodiversity play an important role in such changes.

Biodiversity refers to the number and variety of organisms, at the level of populations, species, and ecosystems (Perman et al., 2011). It is assigned particular importance in the renewal and reorganization of ecosystems after a disturbance, relating to the concepts of resilience and regime shifts (Folke et al., 2004). Folke et al. (2004) distinguish two aspects of diversity, namely functional-group diversity, and functional-response diversity. Functional groups provide services such as pollination and predation. The persistence of such groups contributes to the performance of, i.e., services provided by ecosystems (Folke et al., 2004). Functional-response diversity encompasses the *"... diversity of responses to environmental change among species that contribute to the same ecosystem function"* (Folke et al., 2004, p. 570). Higher levels of response diversity facilitate the preservation of resilience in the face of environmental change, and increase the chances of renewal and reorganization into a desired state after a disturbance occurs (Folke et al., 2004). In sum, biological diversity influences the ability of ecosystems to remain within desired states (Folke et al., 2004), provides evolutionary potential (Perman et al., 2011), and serves as a buffer against ecological collapse (Folke et al., 2004; Perman et al., 2011). The role of biodiversity is of particular importance as human activity tends to maximize harvest in the short-term undermining long-term performance (Hilborn et al., 2003), and has contributed to substantial decreases in the overall diversity of ecosystems (Mace et al., 2005). At the same time, degrading biodiversity in response to human pressures may occur with substantial time-lags (Dullinger et al., 2013), increasing the level of uncertainty about ecosystem functioning.

1.2.3 Environmental Impact

As discussed above, economic activity impacts the environment. However, for most of human history these impacts were, although pervasive, at a scale that could easily be coped with by the earth system (Steffen et al., 2007). This has changed as the scale of human influence has increased dramatically. The IPAT equation is commonly used to determine the driving forces behind environmental impacts and will be discussed as well as some stylized facts about the development of environmental pressures over time.[5]

1.2.3.1 Drivers of Environmental Impact

To determine the level of environmental impact and its proximate drivers the IPAT equation was introduced in the early 1970s (Ehrlich and Holdren, 1972, 1971) and is still used today (Perman et al., 2011; Steinberger et al., 2010; Weina et al., 2016). The equation provides a general formulation for the total level of environmental impact, and in its original formulation by Ehrlich and Holdren (1972), is written as:

$$I = P * A * T \qquad (1)$$

with I representing the total environmental impact, P representing population, A representing affluence, and T representing technology (Ehrlich and Holdren, 1972). More specifically, A is

[5] Note that pressures and impact are used interchangeably within this work. In the subsection on environmental pressures, however, the factors influencing the environment will be organized with more specificity.

production per capita, and technology is the impact per unit of production. Thus, three multiplicative and proximate drivers of environmental impact are defined by the IPAT equation.

However, in its abovementioned form the equation implies the three proximate factors to be independent, although this has been categorically denied (Ehrlich and Holdren, 1971; Holdren, 2018). Alcott (2010) discusses seven interdependencies of the three proximate factors. Alcott (2010) considers the population factor to have two interdependencies. First, affluence is dependent on population size since resource availability per capita is negatively related to an increasing population. Second, technology is also a function of population, as incentives to produce more efficiently are dependent on both the scarcity of resources and the perception of environmental degradation, which increases if less area per capita is available. Three interdependencies have been defined for affluence. First, population is a function of affluence as both reproduction and mortality rates change based on income. Second, it is possible to delineate several interrelations between technology and affluence. Varying levels of affluence might place less pressure on the efficient use of resources, or determine the degree of research and development designed to improve technological and environmental conditions. Third, the real affluence of population subsets interacts. For example, if a subset lowers its consumption, a subsequent decrease of prices might incentivize a different subset to increase consumption. Finally, Alcott (2010) names two interdependencies for technological change. First, population is influenced by the state of technology, as for example improvements in agricultural efficiency support higher population levels. Second, affluence is a function of technology, as more advanced levels of technology are associated with higher levels of wealth.

Beyond these interactions between the variables of the IPAT equation, other interdependencies exist. Varying levels of education and environmental awareness impact consumption and technological design. In a similar way, demographic structures impact lifestyles and consumption decisions (Liddle, 2004; Zagheni, 2011). The interrelation of numerous driving forces, with a strong tendency towards rebound effects (Alcott, 2010), is highly relevant for the assessment of the role of technological changes in the context of environmental impact. Alcott (2010) has suggested that a more accurate postulation of the IPAT equation is:

$$I = f\,(P, A, T) \qquad (2)$$

1.2.3.2 Environmental Pressures

To evaluate the magnitude and development of environmental issues over time, the empirical assessment of sustainability issues relies on the appropriate choice of indicators. In order to define and select these indicators with greater accuracy, a distinction between environmental pressures and impacts is made. The DPSIR framework categorises factors that influence the environment as Drivers, Pressures, State, Impact, and Responses (Smeets and Weterings, 1999). According to the DPSIR framework, emissions, resource, or land use qualify as pressures, not as impacts; although the connection with impacts such as resource availability or biodiversity loss is evident. A different categorization is provided by UNEP (2011), distinguishing between resource and impact indicators. On this basis, the use of land, energy, materials, and water qualify as resource indicators; whereas emissions, water pollution, and biodiversity loss qualify as impact indicators (Parrique et al., 2019). Though all of these indicators focus exclusively on the environmental dimension of sustainability, relevant differences exist. Resource indicators on material, energy, or land use provide the advantage of capturing human dependence on the environment, and the potential of environmental impact. However, each indicator has relevant drawbacks. Material indicators, accounting for each material in tons, cannot account for different impact potentials of the materials (Roman and Thiry, 2017). Energy use has different environmental implications, e.g., concerning CO_2 emissions and land use change, dependent upon the composition of energy sources (Haas et al., 2015). Land use indicators, such as the ecological footprint, do not distinguish the sustainability of its use (Roman and Thiry, 2017). Individual impact indicators also have their idiosyncratic limitations. Biodiversity indicators may suffer from substantial time-lags (Dullinger et al., 2013), while emission indicators necessarily ignore other sources of environmental damage.[6] Hence, to provide convincing evidence for the extent of the sustainability problem, the development of indicators of human activity, and environmental pressures and impacts will be shown. First, we will provide and discuss data on resource indicators, namely: energy and material use. Next, the recognised notion of a 'Great Acceleration' (Steffen et al., 2007) of both human activity and environmental consequences will be discussed, followed by the development of two highly relevant and distinct impact indicators, specifically CO_2 emissions and biodiversity loss. Finally, conceptualizing the interrelatedness of all types of environmental pressures and impacts, and

[6] Other environmental damages include soil erosion, chemical pollution, and other types of environmental impact that cannot be accounted for by an individual pollutant indicator.

their joint dependence in the context of the earth system, the impacts conceptualized as planetary boundaries by Rockström et al. (2009) will be introduced.

As all work requires energy (Schramski et al., 2015), and energy consumption is considered to be very closely interrelated with economic growth (Ayres et al., 2003; Murphy and Hall, 2011), energy consumption is well suited to be an indicator for capturing the biophysical dimension of human activity. As can be seen in Figure 1, global energy consumption has continued to rise during the past 25 years, from less than 9,000 million tons oil equivalent (MTOE) to almost 14,000 MTOE. Fossil fuels play the major role, as in 2018 34% of primary energy stems from oil, 24% from natural gas, and 27% from coal. Hence, ~ 85% of global primary energy consumption is derived from fossil fuels. Nuclear energy constituted roughly 4%. In total, 11% of primary consumption stems from renewables, with 7% generated from hydroelectricity and 4% from other renewables.

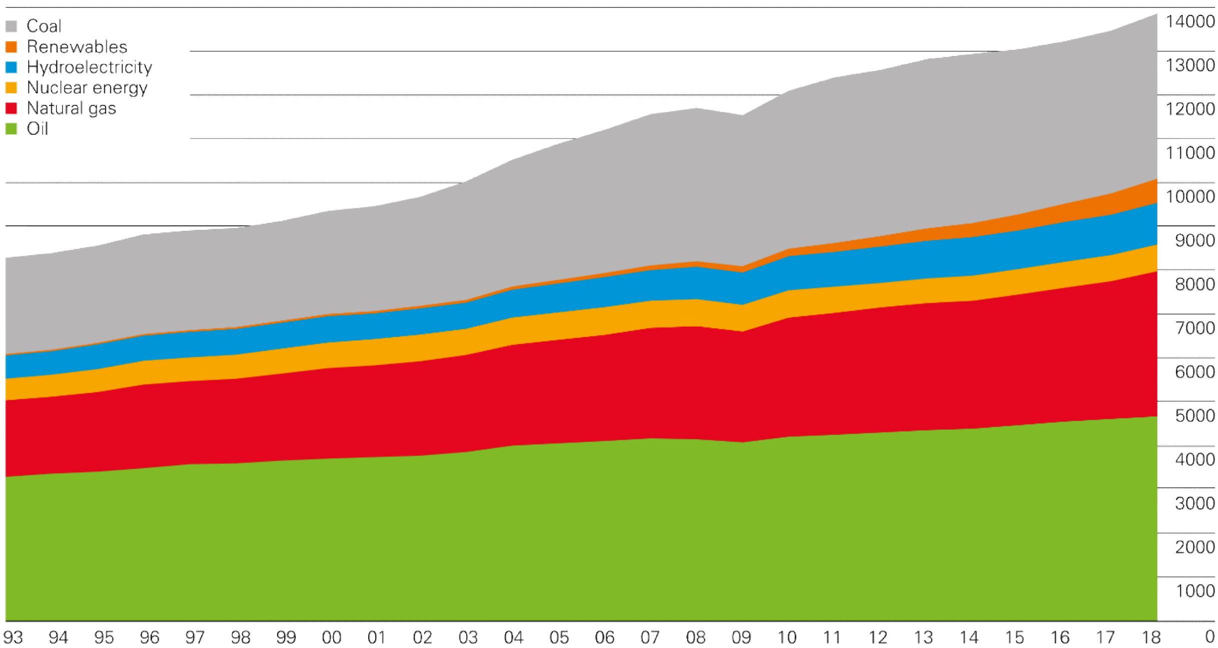

Figure 1: Global primary energy consumption in million tons oil equivalent by energy source, from 1993 to 2018

Source: British Petroleum (2019, p. 10)

Energy, as the fundamental input to carry out work, is directly related to the utilization of other resources such as materials. Figure 2 shows the development of global material extraction from 1900-2005. A substantial increase after World War II (WW II) is well visible, accompanied by some shifts in the composition of material use (Krausmann et al., 2009). In the period from 1970-2010 annual global material extraction tripled to 70 billion tons (UNEP, 2016). Recently, the increase in material extraction is surging again. Krausmann et al. (2018) suggest that material extraction reached 89 Gt/yr by 2015. The rapid growth of extraction between 1945 and

1972 of 3.7% per year was followed by a slow down to 1.8% per year between 1973 and 2002. From 2002-15, however, growth accelerated again to 3.3% per year (Krausmann et al., 2018). A relevant observation from Figure 2, however, is that concomitant with this increase in resource extraction, resource productivity also increased as can be seen by the disproportionate increase in GDP. This also holds for the relation of economic activity and energy use (Steffen et al., 2007), as well as similar dynamics in the case of land use.

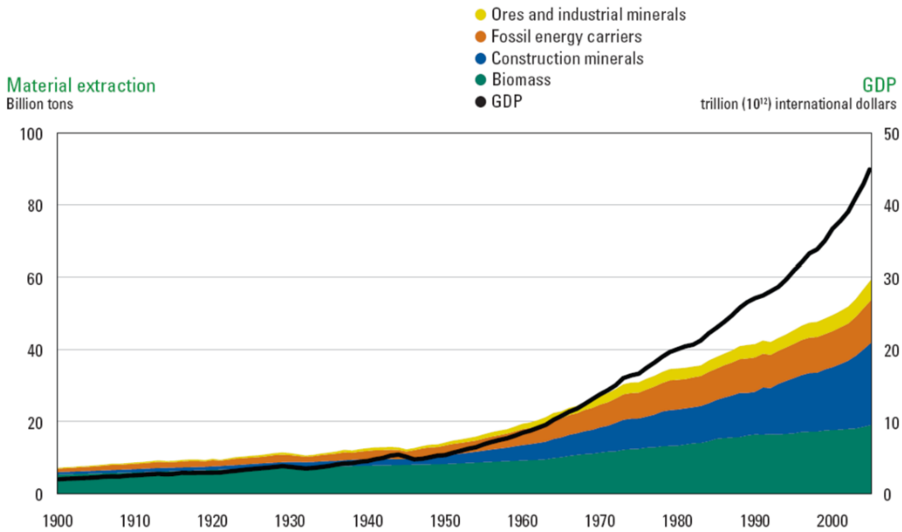

Figure 2: Global material extraction by material class in billion tons, from 1900 to 2005

Source: UNEP (2011, p. 11)

Based on data from: Krausmann et al. (2009)

This increased utilization of resources is not only the driving force behind, but is also driven by what some researchers label as the 'Great Acceleration' (Steffen et al., 2007). The ´Great Acceleration' is a term that might be thought of as encompassing the tremendous increase of human activity in the time following WW II. Steffen et al. (2007) present a wide range of indicators that describe this dynamic, including: urbanization, transportation, and communication. The surge of human activity post-1950 is evident in all indicators, with some areas of human activity, such as international tourism, being virtually irrelevant before 1950 (Steffen et al., 2007). This increase in human activity results in environmental impacts that endanger the functioning of the earth system in supporting human existence (Rockström et al., 2009; Schramski et al., 2015; Steffen et al., 2007). The acceleration in the use of resources and indicators of human activity is also evident in indicators that are driving detrimental environmental change (Folke et al., 2004; Rockström et al., 2009). Figure 3 shows the development of CO_2 emissions, displaying a similar rise after 1950. Although CO_2 emissions capture primarily human activity with expected detrimental environmental effects, the development presented in Figure 4 poses potentially more daunting threats. Figure 4 shows the development of the Living Planet Index, an indicator of biodiversity reported by the World Wide Fund for Nature (WWF). As discussed above, biodiversity is of crucial importance to the stability of ecosystems (Folke et al., 2004), and biodiversity loss is a more systemic result of human activity with potentially large time-lags for reactions (Dullinger et al., 2013). In the 2018 report (World Wide Fund for Nature, 2018), this biodiversity indicator has been estimated to have decreased by around 60% compared to 1970. Although there are substantial differences between the characteristics, driving forces, and impacts of environmental indicators, at the global level most indicators have the similarity that they capture the overall increase of economic activity that is associated with increases in environmental pressures and impacts. Also, despite a trend towards efficiency increase (reduced environmental pressure per unit of economic output), the impact of human activity on the environment has tremendously increased irrespective of the indicator chosen.

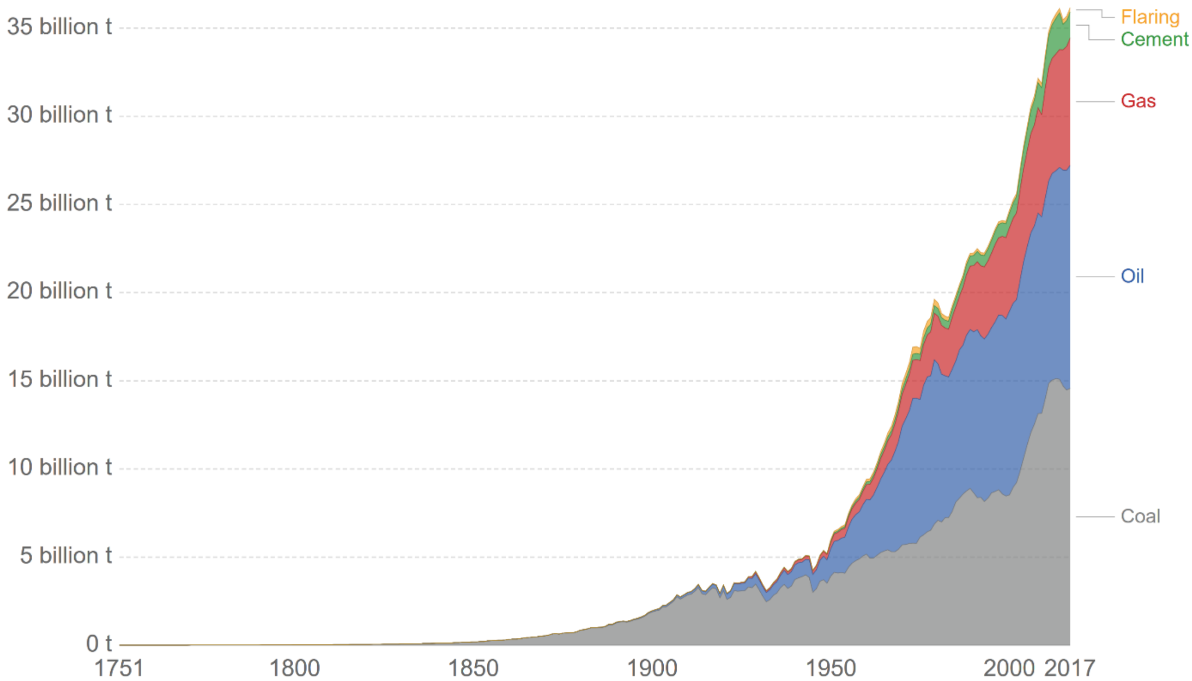

Figure 3: Global CO2 emissions by source in tons per year, from 1751 to 2017

Source: Ritchie and Roser (2019)

Based on data from: Carbon Dioxide Information Analysis Centre (CDIAC) (Boden et al., 2017), and the Global Carbon Project (Quéré et al., 2018)

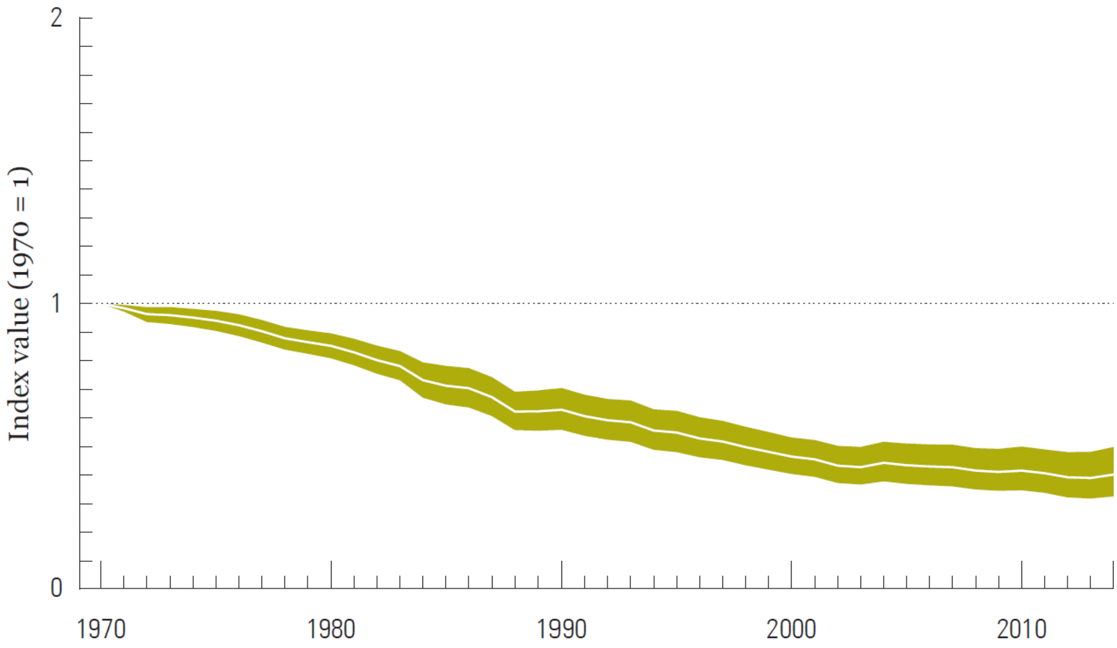

Figure 4: Development of the Global Living Planet Index, from 1970 to 2014

Source: World Wide Fund for Nature (2018, p. 90)

Attempting to conceptualize global sustainability in the context of anthropogenic pressures on the Earth System, Rockström et al. (2009) identify nine planetary boundaries, the crossing of which triggers non-linear and abrupt environmental change (Rockström et al., 2009). These boundaries include climate change, ocean acidification, stratospheric ozone depletion, atmospheric aerosol loading, biogeochemical nitrogen and phosphorus cycle, global freshwater use, land-system change, rate of biodiversity loss, and chemical pollution (Rockström et al., 2009). These processes are further distinguished based on two criteria, namely the existence of sharp planetary thresholds, and whether thresholds occur at the planetary scale ("top down") or at the local/regional scale first ("bottom up"). Both climate change and ocean acidification, on the one hand, have global scale thresholds and affect the earth system top down. Biodiversity loss and chemical pollution, on the other hand, are slow processes that occur on a local/regional scale first, and without well-known global thresholds. The planetary boundaries are interdependent, such that the positions of some boundaries depend on the positions of other boundaries (Rockström et al., 2009). Higher rates of biodiversity loss, for example, decrease the resilience of an ecosystem (Folke et al., 2004) to respond successfully to pressures such as chemical pollution. Except for the boundaries of chemical pollution and atmospheric aerosol loading, Rockström et al. (2009) propose quantifications for each boundary. Based on these quantifications, they find three boundaries that have already been transgressed, namely: climate change, biodiversity loss, and changes to the global nitrogen cycle (Rockström et al., 2009).

These results were largely confirmed by Steffen et al. (2015). Climate change and biodiversity loss, which have both been crossed, are acknowledged to be of fundamental importance for the earth system (Steffen et al., 2015).

To summarise, at the global scale human impact on the earth system has reached a scale at which humans “dominate” the biosphere, and are influencing the earth system in ways that detrimental global environmental change cannot be excluded (Folke et al., 2004; Rockström et al., 2009; Schramski et al., 2015; Steffen et al., 2007). Due to the interdependence of the system components, as well as the existence of thresholds after which positive feedback mechanisms can cause further irreversible changes, there is uncertainty about the consequences for the environment. As shown above, at the global scale an acceleration of human activity and environmental impacts can be observed after WW II. This has triggered the debate on the ‘limits to growth’ (Meadows et al., 1972) and as to whether economic growth can, and should, be further pursued. This ‘growth debate’ will be discussed in the next section.

1.2.4 The Growth Debate

As has been discussed in the context of the IPAT equation, in very simple terms the environmental impact of humanity is contingent upon population, affluence, and technology. In its original multiplicative form, population times affluence constitutes the overall scale of human activity. The fundamental economic debate in the context of sustainability issues revolves around the concept of economic growth, and comprises three main questions (van den Bergh, 2001). First, whether economic growth is desirable, followed by as to whether it is feasible. And third, whether it is controllable, i.e., whether growth imperatives exist. Given the current dependence on and existence of economic growth, the first two questions are relevant in clarifying the prospects of the human species under a ‘growth regime’, whereas the third relates to possibilities and measures to curtail economic growth if it is required.

The desirability of economic growth depends upon the assessment as to whether economic growth is associated with increases of welfare. Some research fields take such positive effects of economic growth for granted (van den Bergh, 2001). Others argue that there are some ‘ethicosocial’ limits (Daly, 1987). Daly (1987) discusses four propositions that limit the desirability of growth. First, if economic growth is achieved by ‘drawdown’, i.e., that stocks of valuable minerals such as fossil fuels are consumed, the costs thus imposed on future generations could limit the desirability of growth. Generally, the utility of future generations is discounted based upon a time preference of present individuals, whereas Daly (1987) proposes that fairness would favour an approach using a Rawlsian "veil of ignorance". According to such, a just intergenerational distribution would be one that representatives of generations would choose if they are uninformed of their position in the temporal sequence. Second, if economic growth is achieved by 'takeover', that is the occupation of other species habitats, the accompanied extinction or reduction of other species may limit the desirability of growth. This issue concerns both future generations and non-human species. On the one hand, the question of intergenerational justice may arise due to the extinction of species and loss of ecological capital, for example in the form of gene pools. This reduces instrumental value concerning the provision of ecosystem services in the future. On the other hand, non-human species, many of which clearly qualify as sentient beings, can be considered of intrinsic value such that their pain and pleasure is of moral relevance and thus needs to be taken into account (Daly, 1987; Singer, 2011). Third, aggregate growth may become undesirable due to self-cancelling effects on welfare. This goes back to the 'Easterlin Paradox', the finding that differences in happiness dependent on income are well visible within a country yet not between countries (Easterlin, 1974). This further requires a distinction between achieving the fulfilment of basic needs and achieving needs that go beyond basic requirements. The improvement of happiness due to fulfilling basic needs remains unchallenged. However, increased happiness may not occur with rising income once basic needs are met, due to relative income being more important than any absolute level. However, in terms of relative income, aggregate growth cannot make anybody better off without making others worse off. Similarly, if happiness improvements are in fact dependent on changes of income there would be pressure to always increase the rate of growth itself in order to achieve such improvements. Further, Hirsch (1976) acknowledges that satisfaction from consumption beyond basic needs is limited as increased competition for 'positional goods' makes satisfaction increasingly dependent upon the consumption of others.[7] Linder (1970) considers increasing time-scarcity, since increased labour productivity makes time relatively more expensive. In sum, the burden of scarcity is shifted by growth to time and relative position. Last, the desirability of growth can be limited due to corrosive effects on moral standards and social foundations exerted by the attitudes and concepts that foster growth (Daly, 1987).

[7] The classic example includes the notion that "if everyone stands on tiptoe, no one sees better" (Hirsch, 1976, p. 5). Similar cancelling effects concern utility derived from education or cars. While the utility derived from the former decreases if more people achieve higher levels of education such that the same position in a hierarchy cannot be obtained, the utility of cars decreases as driving satisfaction and reaching destinations quickly are negatively affected by traffic jams, for instance.

The Limits to Growth report (Meadows et al., 1972) questioned the feasibility of continued economic growth, at least given the conditions present at that time. The rising debate on this feasibility fundamentally relates to the issue of biophysical limits. In this context a distinction needs to be made between economic growth in a monetary sense[8] and growth as a quantitative increase of the scale of physical dimensions (Daly, 1987).[9] As discussed earlier the limited availability of stock resources, the limited availability of energy flows in the form of solar energy, and the dependence on functioning ecosystems impose restrictions on bearable environmental impacts. However, questions on the binding nature of these biophysical restrictions are debated. The distinction between weak and strong sustainability, which relates to the degree of substitutability of 'natural capital' by man-made capital is of crucial importance (van den Bergh, 2001). This concerns the potential to 'decouple' economic growth[10] from environmental impacts. Recalling the IPAT equation, the technological factor is thus of crucial interest. Given that this thesis is fundamentally concerned with the feasibility of economic growth and the decoupling of environmental impacts by means of technological progress, this question will be explored in more depth later.

The third question raised by the growth debate is whether economic growth can be controlled. This relates to whether or not certain macroeconomic goals, such as full employment, are attainable without economic growth (van den Bergh, 2001), i.e., whether growth imperatives exist that cause strategies of zero growth or degrowth to not be feasible. One explanation of a growth imperative is rooted in the monetary sphere (for example Binswanger, 2009; Heinsohn and Steiger, 2011; Löhr, 2012).[11] Richters and Siemoneit (2017) argue against a monetary growth imperative, that is a growth imperative due to the existence of "interest- bearing debt-money with private banks" (Richters and Siemoneit, 2017, p. 114). Instead, they argue that a growth imperative emerges from the dynamics of technology (Richters and Siemoneit, 2019). Starting at the firm level, they argue that due to 'Schumpeterian creative destruction' firms are forced to innovate in order not to lose market shares. Due to the strong coupling of innovation to capital accumulation and hence net investments (Aghion and Howitt, 1998) firms thus must grow. As entrepreneurs are able to reduce costs by relatively cheap factor combinations of

[8] Measured by GDP.
[9] Such as materials or energy consumption.
[10] In monetary terms.
[11] It is not intended to provide an exhaustive and explicit argument on this matter. Hence, it is not sought for an answer as to whether growth imperatives exist, or what the root cause is. Instead, the intention is to provide an orientation concerning frequent explanations. The explanation of Richters and Siemoneit (2019) will be explained in more detail as it puts technological progress center stage. This explanation is prioritized due to the scope of the present thesis.

capital and energy (substituting labour) a general trend toward process automation and a bias towards technical products is established. Hence, a growth imperative at the firm level is constituted by the dynamics of innovation competition, which is driven by increasing resource consumption (Richters and Siemoneit, 2019). On the level of households, they argue that the ability to generate an income is of fundamental importance in a market economy. In order to remain competitive, whilst securing leisure time, households are forced to invest in human capital. Consumption in this sense becomes ‘efficiency consumption’, as it is household investment required to keep pace. Hence, efficiency gains by technological devices provide a similar growth imperative as at the firm level (Richters and Siemoneit, 2019). Richters and Siemoneit (2019) suppose that these growth imperatives expand to the level of nation states due to a threefold interplay of technological unemployment, the societal obligation to guarantee a minimal standard of living, and the meritocratic principle that prohibits direct redistribution as a matter of justice. Given the impossibility of prohibiting technical change, growth as a means of securing high employment is intruding, in order to provide the required standard of living (Richters and Siemoneit, 2019). However, despite these observations institutional arrangements are considered to have the potential of influencing such growth imperatives (Richters and Siemoneit, 2019).

1.3 Technology and the Environment

It can be derived from the previous section that in the context of the long-term compatibility of human development and environmental limits, technology is of pivotal importance. Given the focus of the present thesis on technology and sustainability, this section will discuss the interrelations of these spheres in an integrated way. First, fundamental characteristics of technologies and technological change will be introduced, including the motives and directing forces of technological progress, as well as the opportunities and risks emerging from technological progress. Second, an overview on the historical development of human societies and technologies will be provided, given their mutual dependency. Third, the dynamics and prospects of technological change will be reviewed based on the former and current dynamics of technology development, as well as the scope for further technological progress and its environmental benefits.

1.3.1 The Nature of Technology and Technological Change

In standard economics, technology describes the technically feasible transformation of a set of inputs into a certain level of output (Jaffe et al., 2002).[12] Technological change is then represented by changes over time, such that higher levels of output at given levels of input are feasible (Jaffe et al., 2002). Technological change can be ´neutral´, that is, increased output without changes of relative productivities of production factors, or ´biased´, that is, changes in relative productivities of the various inputs (Jaffe et al., 2002). This process of technological change is constituted by three stages, namely: invention, innovation, and diffusion (Schumpeter, 1942). The impact of technologies stems from all of these stages, such that these are jointly referred to as the process of technological change (Jaffe et al., 2002). Although technology can refer to the whole of technologies being applied with certain shares by a society, when speaking of technologies in this context it refers to individual technologies, such as specific production processes. Innovation, in a broad understanding, refers to the introduction of novelty, either by improving existent technologies or by introducing new technologies. Innovation is dependent upon inventions paving the way, and exerts a substantial impact on the overall technological state, i.e., constituting technological change only when diffusion takes place.

Technological change occurs within a wider system in which it is embedded, and occurs along certain paths due to this embeddedness. Nelson and Winter (1977) defined the concept of a 'technological regime', which relates to a cognitive dimension of the beliefs of technicians concerning the feasibility and worthiness of attempts. Dosi (1982) introduced the distinct concepts of 'technological paradigms' and 'technological trajectories`. A technological paradigm consists of *"an 'outlook', a set of procedures, a definition of the 'relevant' problems and of the specific knowledge related to their solution"* (Dosi, 1982, p. 148). Further, the concept of progress is defined specifically by a technological paradigm. Technological trajectories refer to the direction of advancing within the technological paradigm (Dosi, 1982). Accordingly, continuous changes occur due to progress along a technological trajectory, whereas discontinuities are based on the emergence of a new paradigm (Dosi, 1982). Dosi

[12] Note that this definition is very specific and that more nuanced definitions could be given (see Grunwald, 2018). A definition that accounts for human activities in which specific technologies are utilized aligns with the technology factor in the IPAT equation, as the T parameter does not stand for technically feasible efficiency, but encompasses the sum of technology choices a society makes (Steinberger et al., 2010). Thus, the narrow definition of technological change, based upon technological progress, should be considered distinct from practical changes of a technology parameter as present in IPAT, since real technology choices do not only encompass technical feasibility, but also social, economic, and historical causes.

(1982) emphasizes that the pursuit of progress is thereby not randomly making use of all *"notional technological opportunities"* (Dosi, 1982, p. 158). Incremental innovation, according to Dosi (1982), occurs as normal technological progress along a trajectory, whereas radical innovation relates to the emergence of new technological paradigms.

Freeman and Perez (1988) suggest a more detailed taxonomy of innovation. This introduction of novelty into the technological state of societies is distinguished by four different types: incremental innovation, radical innovation, new technology systems, and changes of techno-economic paradigms. Incremental innovations are considered to occur rather continuously, due to for example learning-by-doing processes. These contribute to the steady growth of productivity by improving the efficiency of all production factors (Freeman and Perez, 1988). Radical innovations are considered to be discontinuous events as a result of research and development (R&D). They do not emerge from improving current production processes, but can initiate the growth of new markets. Although radical innovations induce structural change, the overall impact remains small and localised, unless a cluster of radical innovations introduces new industries and services (Freeman and Perez, 1988). In contrast, changes of a technology system require far-reaching changes of technology, with effects on several economic branches, and giving rise to the emergence of new sectors. This is driven by a combination of innovations that are technically and economically interrelated (Freeman and Perez, 1988). Changes of 'techno-economic paradigms' require effects on the entire economy, due to many clusters of innovations, and eventually a number of new technology systems. It has to, directly or indirectly, affect the whole economy beyond changes of specific trajectories by influencing production and distribution throughout the system (Freeman and Perez, 1988). Within a new techno-economic paradigm, either a particular input factor or a set of inputs needs to fulfil three criteria, in order to act as key factor of the new paradigm. First, low relative costs that are rapidly falling have to be clearly perceived. Second, seemingly unlimited supply over long periods has to be provided. And third, the potential to use and incorporate the new input factors throughout the economic system has to be obvious (Freeman and Perez, 1988).

As has been argued above, the path of technical progress takes place under restrictions concerning the problems that are tackled, and the approaches that are used. Of central importance for this are the reasons why innovative activity is undertaken, and which incentives focus human resources on the solution of specific problems. Hicks (1932) considered the role of relative prices to be of crucial importance, as changes in relative prices should spur inventions to economize the use of the relatively more expensive factor. In a similar vein, Schmookler (1966) argued that demand is the main determinant of invention. However, it has also been argued that economic forces and market mechanisms are not of primary importance as a mechanism for inducing technological change (Rosenberg, 1969). Specifically, scientific discoveries can also provide stimulus for technical change (Ruttan, 1971). Further, Rosenberg (1969) argues that technologies themselves, especially when being sufficiently complex and interdependent, generate signals and compulsions that direct the search for improvements. The responses to these compulsions generate a compulsive sequence caused by imbalances. In response to a signal, the target mark tends to be surpassed, such that within an interdependent system an incentive is created towards changes at other points in the system (Rosenberg, 1969). Therefore, technological change is to some degree a self-generating process. Rosenberg (1969) identifies further inducement mechanisms of technological change. The supply of workers may act as an inducement mechanism, either due to worker non-compliance and strikes, or due to an inelastic supply of skilled labour, such that effort is directed towards substituting labour (Rosenberg, 1969). Further inducement mechanisms can stem from the political and/or natural sphere. For example, if the supply of specific inputs is reduced or stopped, or if acts of legislation impose constraints (Rosenberg, 1969).

The effects of technical progress have a dual nature. On the one hand, technologies have positive effects, such as increases of efficiency and possibilities of substitution, enabling the discovery of natural resource reserves, and offering the potential of fundamental technological change (Foray and Grübler, 1996). The development and application of new technology was necessary for human development and economic evolution. The utilization of non-anthropogenic energy sources (Cordes, 2009) and finding new uses and solutions (Ayres, 1989) have facilitated human development. Such technological advancements were characterized by gaining independence of natural restrictions, be it in terms of relieving energy restrictions (Cordes, 2009), or eradicating external variations to improve predictability (Tiles, 2009). However, with the initial choice of technologies potentially occurring due to historical events, technology choices may prove to be inferior compared with alternatives (Arthur, 1989). Due to the path-dependency of technological processes, an inferior technology choice may be locked-in (Arthur, 1989; David, 1985), such that the more efficient technology does not prevail. David (1985) considered technical interrelatedness, economies of scale, and quasi-irreversibility of investment to have caused lock-in. These characteristics can be subsumed as 'network externalities' (Ruttan, 1996), referring to the dependence of the utility gained by an adopter on the previous choices of other adopters. This applies for example to infrastructure such as railways, or the use of social media. Arthur (1989) emphasized the crucial importance of increasing returns to scale as a source of lock-in to an inferior technology. Furthermore, technological developments are generally associated with unintended and unanticipated side-effects (Gray, 1989; Grunwald, 2018). Negative consequences are often an integral part of any new technology, such that new technologies constitute both the cure of some and the cause of other problems (Ausubel, 1989). In a similar vein to the inducement mechanisms postulated by Rosenberg (1969), the potentials and limitations of many new technologies have the characteristics of being somewhat set from the beginning, such that technological necessities to solve the arising limitations emerge (Ausubel, 1989).

The characteristics of technology provide the basis for some regularities in technological development (Ausubel, 1989). 'Network externalities' and learning curves provide reasons for the diffusion of a technology, whereas negative consequences such as resource depletion may foretell limits of a technological system. The diffusion of a technology typically follows an S-shaped curve (Ausubel, 1989). That is, technologies in early development are slow to gain acceptance, then there is a phase of rapid diffusion and expansion, until a point of saturation or senescence is reached (Ausubel, 1989). In the context of substitution following such patterns, when a new technology replaces an old one indicated by changes in market shares, a structural change occurs (Ausubel, 1989). While these dynamics can have different durations, dependent on the technology, fundamental shifts of technologies and 'techno-economic paradigms' (Schumpeterian long waves) have been found to occur at approximately 50 year intervals over the past two centuries (Ausubel, 1989). Ausubel (1989) finds such intervals to have occurred for example in the emergence of transport infrastructures or the dominance of a major energy technology. Freeman and Perez (1988) distinguish five long waves since the onset of the Industrial Revolution. The first wave (~1780-1830) corresponds to the Industrial Revolution, associated with the textile industry, iron, and water power.[13] The second wave (~1830-1880) consists of the Victorian prosperity, associated with steam power and railways. The third wave (~1880-1930) was primarily characterized by steel as the key factor, and is associated with electricity and the automobile. The fourth wave (~1930-1980) is characterized as the 'golden age of growth' and the consumer society, with especially oil as key factor. It is also associated with mass production. The fifth wave (~since 1980) is characterized by the crucial role of information and communication, associated with digitalization (Freeman and Perez, 1988).

Technology choices are of pivotal importance, due to the systemic nature of technologies, and their relation to the survival or collapse of civilizations (Diamond, 2005; Rosenberg, 1971;

[13] Note that these are just a few exemplary mentions, although there are many more key characteristics of each wave, see Freeman and Perez (1988).

Tiles, 2009). Technologies, acting as an intermediary, create environments as human-natural hybrids, by influencing the physical, socio-economic and political environment that emerges (Tiles, 2009). Hence, technological advancements do not appear and act in isolation, but are themselves existing, thriving, and dying out in mutual dependence on the natural, social, and technological conditions (Tiles, 2009). Once a society comes to depend on certain technologies, these technologies shape and constrain that society (Tiles, 2009). An example of this dependence is agriculture. The increased provision of food caused by agricultural development enabled increases in population size. This constitutes an irreversible choice, since maintaining increased population levels would be impossible without continued agricultural development (Tiles, 2009). Hence, continuing agricultural developments necessitate technological advances in order to increase production levels to satisfy the demand of larger populations, in spite of potential issues caused by these advancements (Tiles, 2009). In effect, the application of technologies and/or the achievement of large scales[14] can be closely related to the subsequent collapse of civilization (Diamond, 2005; Rosenberg, 1971). In this context, the nature of technologies as "infrastructural networks" (Tiles, 2009) demands consideration. As such, technologies form a system that is not self-sustaining, but can impose high maintenance burdens, potentially rendering the system vulnerable to collapse (Tiles, 2009). Due to the increased impacts of technological consequences given a more densely populated planet (Gray, 1989; Rosenberg, 1971), these emergent problems caused by the use of technology pose large-scale systemic risks (Weizsäcker and Wijkman, 2018).

In summary, there are a variety of reasons for the emergence of technological advancements. Economic forces begging for higher levels of efficiency or substitution possibilities may drive certain types of technological advancements. Certain natural forces also come to bear, as humans strive to remove restrictions created by the natural environment. Inherent dynamics of technology, or political forces can also take effect. Technology itself can be thought of as a transformative force that always looks for newer and better ways of accomplishing a task. In this way, technologies shape the environment from which new technological opportunities and necessities emerge. Technological change takes on different magnitudes. Regular technical progress within specific trajectories primarily tends to exploit maximum efficiency under given settings. On the other hand, at larger time-scales discontinuous technical progress based on new input factors, is associated with causing fundamental changes in the institutional sphere. Due

[14] Large scales of population and wealth with the associated environmental impacts.

to historical events, inferior technologies may succeed. As technologies alter the environment, their use can either facilitate or undermine the very basis and development of societies.

1.3.2 Technology and Human Development

The historical interrelation of technological and human development, and the associated environmental impacts, will now be introduced in more depth, drawing on the concept of 'socio-metabolic regimes', a concept referring to a society based on the flows of materials and energy and related processes that humans control for reproduction and the evolvement of their societies (Pauliuk and Hertwich, 2015). Using a historical perspective, we will first introduce certain developments before the Industrial Revolution, followed by developments after the Industrial Revolution.

1.3.2.1 Technology and Preindustrial Development

Historically, technology has been of crucial importance. New technologies allow humans to use different types of energy sources and other natural resources, enabling societies to develop far beyond their initial conditions. Before humans engaged in the large-scale utilization of fossil fuels (approximately 250 years ago) that sparked the industrial-fossil economy, humans already used specific technologies and resources that enabled societal development. However, the scope of human activities and the associated environmental impacts were negligible when compared with industrial societies (Steffen et al., 2007). Before the emergence of industrial societies, two broad societal types can be distinguished (Fischer-Kowalski et al., 2014; Haberl et al., 2011). Hunter-gatherer societies were prevalent until being replaced (approximately 12,000 years ago) by agricultural societies (Fischer-Kowalski et al., 2014). The rise of agricultural societies eventually led to the development of industrial societies. These three societal types are considered to be fundamentally distinct 'socio-metabolic regimes' (Haberl et al., 2011). We will introduce the socio-metabolic regimes of hunter-gatherer and agricultural societies, including the role of technological development and the resulting environmental impacts.

Prior to the advent of agriculture humans lived as hunter-gatherers subsisting on foraging (Haberl et al., 2011). Although humans did not systemically alter their environment at a global scale, the development of means for increased survival chances gave rise to humans' impact on the environment. Nevertheless, humans remained dependent on the passive utilization of solar energy (Fischer-Kowalski et al., 2014). Technologically relevant developments encompass the development of tools, the utilization of fire, and the domestication of animals (Steffen et al., 2007). The use of fire to prepare food greatly enhanced human cultural evolution. This process increased both the variety of usable food and the efficiency of digestion, as well as stimulating social cohesion and communication (Fischer-Kowalski et al., 2014). The shift to an omnivorous diet gave rise to substantial increases in brain size (Steffen et al., 2007). Predation and the modification of landscapes (often through the use of fire) by humans caused widespread environmental impacts. These impacts, however, were neither significant on a global scale, nor followed a systemic pattern (Steffen et al., 2007).

The Neolithic Revolution[15] fundamentally altered the relationship of humans with their natural environment. The beginning of agriculture and animal husbandry is associated with the systemic utilization and alteration of the natural environment as agrarian ecosystems were created (Haberl et al., 2011). In this way, humans actively utilized solar energy by clearing natural vegetation to increase the net primary production to be used for human purposes (Fischer-Kowalski et al., 2014). These developments roughly coincided with the development of written language, promoting learning and the accumulation of knowledge (Steffen et al., 2007). The domestication of animals allowed humans to access animals' work as an additional source of energy. The technological advancement of mechanically harnessing natural forces, including the use of windmills and waterwheels, is another example of accessing natural sources of energy (Cordes, 2009). The introduction of the printing press in the 15th century increased the pace of technological evolution, as the storage and distribution of knowledge became much cheaper and more widely available (Cordes, 2009). However, in spite of the ongoing sophistication of machinery and technology, these advances remained constrained within agrarian societies. Land and physical labour remained the principal complementary inputs (Cordes, 2009). Despite the use of charcoal, water, wind power, and some highly localized uses of coal (Malm, 2013; Steffen et al., 2007), agrarian societies depended almost entirely on the energy supply of biomass from agricultural and forestry ecosystems (Haberl et al., 2011), and physical energy of human agents (Cordes, 2009). Hence, growth remained fundamentally constrained by area-bound energy flows and humans' capacity for physical labour.

Table 1 displays characteristic values for all three socio-metabolic regimes. The shift to agrarian societies facilitated substantial increases in the utilization of materials and energy, and a substantially denser population. Nevertheless, societal organization remained mainly dependent upon using biomass, and humans were, for the most part, engaged in agricultural activities.

[15] Dated back to have occurred roughly 12,000 years ago (Haberl et al., 2011; Steffen et al., 2007).

These restrictions were annulled by the evolution of an industrial society. In addition, from a global perspective population growth before the Industrial Revolution was comparatively negligible. Hence, the global environmental impacts of human societies that were enabled by their technological possibilities and societal organization remained tolerable under both hunter-gatherer and agrarian regimes (Fischer-Kowalski et al., 2014; Haberl et al., 2011; Steffen et al., 2007).

Table 1: Metabolic profiles of typical societies by socio-metabolic regime

	Unit	Hunter-gatherer	Agrarian	Industrial
Total energy use per capita	GJ/cap/yr[16]	10-20	40-70	150-400
Material use per capita	t/cap/yr[17]	0.5-1	3-6	15-25
Population density	Cap/km^2	0.025-0.115	<40	<400
Agricultural population	%	-	>80	<10
Biomass (share of energy use)	%	>99	>95	10-30

Source: adapted from Haberl et al. (2011, p. 2)

1.3.2.2 Technology and the Industrial Regime

The energy bottleneck constraining agrarian societies was shattered by the onset of the fossil economy (Malm, 2013; Steffen et al., 2007). The possibility of utilizing fossil fuels represents the annulment of energy constraints placed on agrarian societies. It also represents the appropriation by modern societies of an energy source originating from the Carboniferous (Steffen et al., 2007). The capability of using fossil fuels is based on a technological breakthrough provided by James Watt, as the refinement of the steam engine leveraged the latent energy in coal to become a universal fuel for commodity production through its transformation into mechanical energy (Malm, 2013). The industrial regime can be primarily characterized by the 'affluence of energy' created by the large-scale utilization of fossil fuels (Fischer-Kowalski et al., 2014; Haberl et al., 2011). The use of fossil fuels as the primary source of energy is a fundamental distinctive characteristic of industrial regimes. This characteristic is in sharp contrast to the previous regimes that relied on biomass as their primary energy source (Fischer-Kowalski, 2011). The rise of industrial regimes also corresponds to the onset of the Anthropocene (Crutzen and Steffen, 2003; Steffen et al., 2007),[18] due to the environmental

[16] Gigajoule per capita and year.
[17] Tons per capita and year.
[18] To consider the 'Anthropocene' its own geological epoch has been contested for various reasons, which the author largely shares. For the course of this essay, the term is merely used to stress the qualitatively new. relevance of one individual species, and the resulting responsibility for the state of the environment. From this perspective, assigning the start of the 'Anthropocene' to large-scale utilization of fossil fuels is useful.

impacts caused by humans using larger amounts of energy made available through technological advancements.

Steffen et al. (2007) distinguish two distinct modes for the Anthropocene: the industrial era from 1800-1945, and the ‘Great Acceleration’ from 1945 to the present day.[19] The industrial era´s enormous expansion in the use of fossil fuels, was initially based on coal. This was followed by the integration of oil and later gas as well (Ausubel, 1989; Steffen et al., 2007). The abundant availability of energy is closely associated with the appearance of new technologies, such as the internal combustion engine. In turn, new technologies rely on specific energy sources that increase in relative importance (Scott and Häfele, 1990). The development of new technologies and the utilization of abundant energy, e.g., to synthesize ammonia from atmospheric nitrogen, laid the foundation for the second phase (Steffen et al., 2007). The Great Acceleration after WW II was dominated by the use of petroleum. Technological developments based on the use of petroleum can be seen in the automobile, the growth of electricity, and the industrialization of agriculture (Fischer-Kowalski, 2011). The combination of a new institutional regime supporting economic growth (Steffen et al., 2007), and technologies that improved mobility and communication drove the globalization of economies. In effect, within 50 years the economy increased more than 15-fold, and population doubled (Steffen et al., 2007). These dynamics were driven by an ongoing transition from agrarian to industrial regimes (Haberl et al., 2011). In agrarian regimes slow technological innovation drives population growth, while in industrial regimes fast innovation drives affluence. The confluence of agrarian and industrial regimes during this phase incentivized the ‘Great Acceleration’. Industrial regimes enabled growth in affluence, while at the same time technology transfers, such as medical advancements or improved modes of transportation, supported the majority of people living in agrarian regimes, and thus allowed rapid population growth – jointly making up the ‘Great Acceleration’ (Fischer-Kowalski et al., 2014).

[19] Steffen et al. (2007) discuss three stages of the Anthropocene, presuming that a third stage, at which humans are actively perceiving their environmental impact and take choices upon how to tackle these issues, should begin at around 2015. However, these future perspectives are outside the interest of this paragraph.

1.3.3 Interactions of Technology and the Environment

Based on these considerations, it is evident that technological advances have been the foundation of human development. At the same time, the large-scale utilization of these technologies has led to a rapid increase in the environmental impact of human activities. Given this reality, it is appropriate to discuss some relevant long-term outlooks concerning the ongoing interplay between technologies and human development. First, some stylized considerations concerning the dynamics of technology/environment relationships will be discussed. Then, the crucial role of technology will be discussed in the context of decoupling and its prospects. Finally, the concept of green technologies and directed technical change as vehicles to shape the technology/environment relationship will be introduced.

1.3.3.1 Dynamics of Technology and Environmental Impacts

Environmental crises are intimately related with technological advances. As progress is made in providing inputs to human society, environmental problems ensue. This is especially the case if technological and institutional change in the treatment of outputs (such as waste) lag behind (Ruttan, 1971). Choices may be made that have negative environmental consequences, in spite of technological alternatives, simply to minimize the direct costs of production (Rosenberg, 1971). Such choices seem to arise from the fact that environmental degradation often qualifies as a negative externality. In other words, society provides economic incentives to overstrain production since the negative consequences borne as social costs by the public are not internalized in the private costs imposed on a market actor for production (Ruttan, 1971).

Such undervaluation of environmental services can lead to biased technological change that reinforces negative environmental consequences. Technical change induced by relative factor prices under economic growth will be biased, such that demand for a resource priced below its social cost grows more rapidly, as the other production factors are sought to be substituted for (Ruttan, 1971). While energy is often not specifically accounted for due to low factor costs (Richters and Siemoneit, 2019), economic growth and energy use are, nevertheless, strongly coupled (Csereklyei et al., 2016), given complementarity of useful energy and capital (Kander and Schön, 2007). Richters and Siemoneit (2019) argue that due to technological constraints there is no immediate substitution of labour with energy and capital, so that factor combinations of capital and energy, while substituting routine labour, are relatively cheap. This cost advantage is presumed to establish a general inclination toward process automation and a bias towards technical products, i.e., increases in resource consumption are economically attractive (Richters and Siemoneit, 2019). The average energy intensity of labour has, indeed, increased over time (Semieniuk, 2018). Hence, there seems to be a complementarity of human capital and natural resources (Richters and Siemoneit, 2019). As a consequence, competition and innovation (i.e., technological change) is being driven by increases in resource consumption (Richters and Siemoneit, 2019; Ruttan, 1971).

These considerations seem to correspond with the fact that most resources pass through the economic system rather quickly, and are lost due to dissipative uses (Ayres, 1989). Similarly, environmentally favourable technologies may not be used in order to keep the costs of production lower (Rosenberg, 1971). Arguing from a historical perspective, Fischer-Kowalski et al. (2014) consider increased environmental pressure as being caused by technology´s facilitation of the shift from biomass to fossil fuel use. Hence, the intention of technological change were not effectively directed towards the solution of environmental problems (Foray and Grübler, 1996; Rosenberg, 1971; Ruttan, 1971). Nevertheless, it can be shown that technologies have contributed to substantial alleviations of environmental problems (Ausubel, 1989), and some authors argue that long-term regularities and trends pose a more favourable role of technological change (amongst others, Ayres, 1989; Foray and Grübler, 1996; Popp et al., 2010; Ruttan, 1971; Scott and Häfele, 1990). Ausubel (1989) considers the overall consistency and stability of the evolution of favoured energy sources and technologies of the past two centuries. Globally, energy sources moved from wood, to coal, to oil, and then to natural gas (Ausubel, 1989). This can be considered a steady development to a substitution of hydrogen for carbon in the long-run (Ausubel, 1989; Ayres, 1989; Scott and Häfele, 1990). Such evolution is considered to be driven by existing limits of each energy form when it dominates an industrial paradigm, such that shifts to economically and environmentally favourable energy sources become inevitable (Ausubel, 1989). Thereby, it can be suspected that as economic incentives drive technological innovation, and thereby the evolution of industrial processes, a long-run trend could be towards technologies that encourage environmental benefits (Ayres, 1989). This presumption can be derived from the increasing importance of environmental quality in more affluent societies (Ruttan, 1971).

These considerations of improving technologies and environmental quality, as well as the consideration that technologies need to be developed towards environmental compatibility will now be discussed in more depth.

1.3.3.2 Technology Effects and Prospects of Decoupling

Drawing upon the IPAT hypothesis and given the rising levels of population and affluence, the only way for environmental impact to not develop accordingly is to change how efficiently affluence is provided. Similarly, from the presumption that as income rises preferences for environmental quality increase, technological change will consequently aim at environmental improvements (Rosenberg, 1971; Ruttan, 1971). This has been most clearly formulated in the so-called ‘Environmental Kuznets Curve’ (EKC) hypothesis, suggesting an inverted U-shaped curve for the relation of per capita income on the horizontal axis, and environmental degradation on the vertical axis. The EKC hypothesizes that initially, as affluence grows, environmental impact grows, yet at a declining rate. At some point of income and environmental impact, the curve reaches a turning point, after which increases of income are associated with improvements of environmental quality. This empirical observation for specific countries, timeframes, and environmental indicators (Stern, 2004) has led to the hypothesis of an EKC relationship that indicates further economic growth to actually be environmentally beneficial (Parrique et al., 2019).

The EKC hypothesis directly relates to the commonplace concept of ‘decoupling’ (UNEP, 2011). It refers to the development of economic activity and environmental indicators not being proportional. ‘Relative decoupling’ refers to a situation in which the environmental parameter grows at a lower rate than the economic indicator, that is increases in the GDP to impact ratio, yet with environmental impact still growing (UNEP, 2011). ‘Absolute decoupling’ refers to reductions of the environmental indicator, despite or irrespective of the growth rate of the economic driver (UNEP, 2011). The EKC encompasses both of these types of decoupling, with absolute decoupling occurring behind the turning point income. Rising income likely relates to increasing environmental awareness (Ruttan, 1971), such that regulation and other underlying causes (Stern, 2004) create shifts in the proximate drivers of an EKC relationship. These proximate drivers include scale effects, structural change, changes in input mix, and direct technological improvements (Stern, 2004). All of these aspects are directly related to production technologies. Structural change occurs when innovations generate new products and facilitate the satisfaction of certain requirements at lower costs (Kander, 2005). Changes in input mixes directly refer to the substitutional possibilities derived from the technological state and improvements (Foray and Grübler, 1996; Ruttan, 1971; Stern, 2004). Direct technological improvements relate to making a production process more efficient (Stern, 2004).

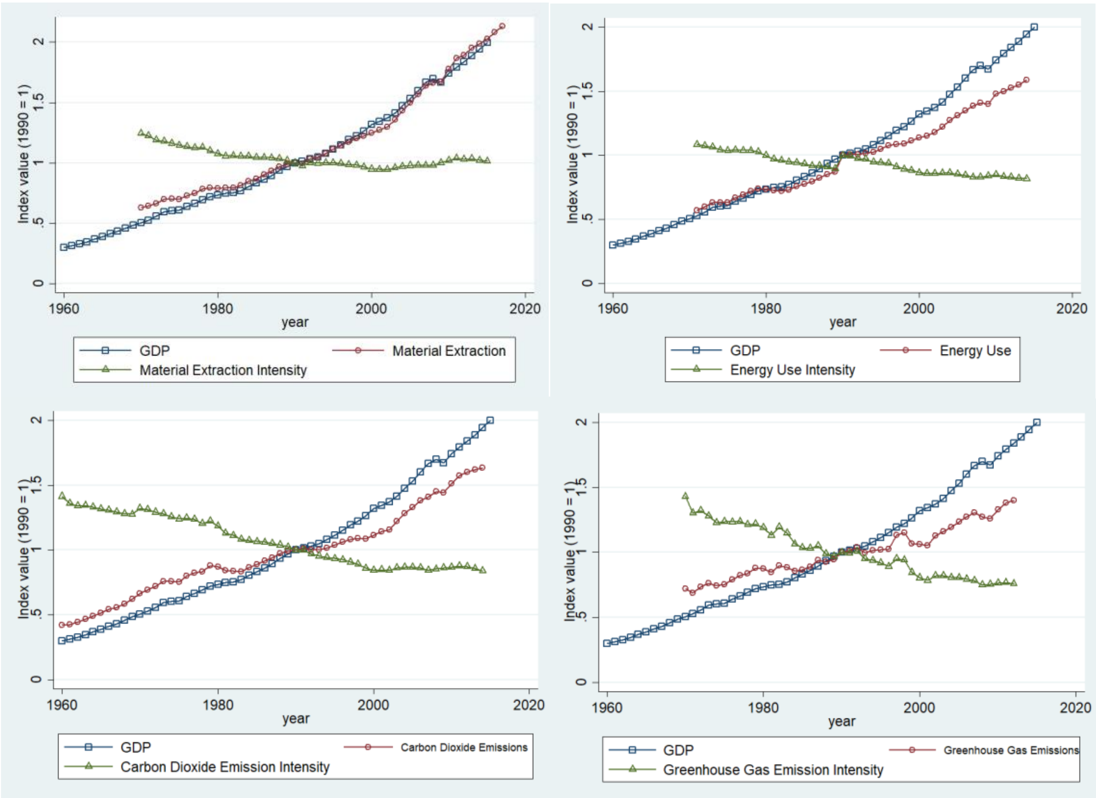

Figure 5: Global dynamics of economic development and environmental indicators, from 1960 to 2017

Source: own elaboration

Based on data from: UNEP Global Material Flows Database (UNEP, 2016), and World Bank World Development Indicators

The graphs above show that, at the global level, relative decoupling has occurred rather consistently over the past decades. Each graph displays a resource (materials and energy) or impact indicator (carbon dioxide and greenhouse gas emissions) alongside global GDP and the derived intensity that is the environmental pressure per unit of GDP. All indicators were normed by their value in 1990. Hence, it can be seen that global GDP has doubled from ~1970-1990 and again between ~1990-2015. The environmental pressure per unit of GDP has a declining trend for each of the considered indicators. An apparent exception is material use, where the material intensity has remained almost unchanged since 1990. The decline in energy intensity also remains rather moderate. More pronounced decreases in intensities can be observed for both emission indicators, especially in the case of greenhouse gas emissions. These graphs show two relevant facts. First, absolute values of resource and impact indicators increase over time. Second, the environmental intensities tend to decline, that is there are successes in relative decoupling. As these observations and the theoretical considerations around the EKC hypothesis suggest, decoupling is an occurring phenomenon, of which the magnitude determines whether absolute decoupling can be achieved. Many studies have analysed decoupling dynamics, with some findings of absolute decoupling (amongst others, van Caneghem et al., 2010; Wood et al., 2018; Wu et al., 2018; C. Zhang et al., 2017), and common findings of relative decoupling (amongst others, Moll et al., 2005; UNEP, 2011; van Caneghem et al., 2010; Voet et al., 2005; Wood et al., 2018; Wu et al., 2018). Decoupling developments may be partially driven by structural change and changes in the input mix, independent of technological change. Yet, the crucial source of these developments is the potential of tremendous technological progress towards more efficient types of uses (Asafu-Adjaye et al., 2015; Weizsäcker, 2011). The importance and realization of substantial decoupling successes by means of technology have readily been taken on by international organizations, in the pursuit of green growth (Altenburg and Assmann, 2017; OECD, 2011; United Nations, 2015; World Bank, 2012).

Despite existent successes, the reliance on decoupling mechanisms in order to achieve sustainability are subject to heavy criticism. While the presence of decoupling in studies is a statistical phenomenon, in the context of the sustainability issue multiple criteria are demanded to be sufficed. This includes that decoupling must be absolute and overall, that is reductions of environmental impacts of all sorts. Further, it needs to take place at a global scale and occur permanently, that is not at some points in time with increases of environmental impacts at other times. Moreover, the magnitude of decoupling has to be sufficient, such that critical thresholds are not surpassed (Parrique et al., 2019). Parrique et al. (2019) consider that cost shifting, that is the externalisation of negative environmental impacts to other regions, has been a common reason for regional decoupling successes. Further, structural change as a means to decoupling also quickly approaches limits, due to limits of increasing the share of services in the economy (Kander, 2005; Parrique et al., 2019), as well as the dependence of the service sector on material goods and infrastructures (Parrique et al., 2019; Steger and Bleischwitz, 2011). Further, the merits of technological change require substantial guidance to contribute to substantial decoupling including the avoidance of rebound effects (Binswanger, 2001; Freire-González, 2017), biases that lead technological change not to be environmentally favourable, a too slow pace in large-scale changes, and substantial side-effects such that problems are merely shifted (Grunwald, 2018). Furthermore, proposals of a circular economic structure in order to deal with resource scarcity and waste issues tends to shift issues to the energy domain, as such proposals crucially depend on availability of large amounts of energy (Cullen, 2017). These aspects pose severe constraints on the feasibility of the required type of decoupling to occur. On a more conceptual level, Common (1995) has shown that if environmental impact per unit of output cannot be decreased to zero, but only to a minimum level above zero due to constraints imposed by thermodynamic laws, in the long-run further economic growth is indispensably related to increases of environmental impact.

Despite the limitations of technological solutions there is a general consensus that technological change is not fully realizing its potential to contribute to sustainability (Popp et al., 2010; Rosenberg, 1971; Ruttan, 1971). This line of argumentation suggests that market failures inhibit sufficient amounts of effort to be made in the deployment of technological potential in the context of environmental issues (Popp et al., 2010; Rennings, 2000). However, two relevant conclusions can be drawn. First, different technologies provide different degrees of environmental advantages, such that some technologies should be, from an environmental perspective, preferred (Kemp and Pearson, 2007; Popp et al., 2010; Rennings, 2000). Second, as technological change is responsive to incentives, there is a scope to direct technological change towards environmental goals (amongst others, Acemoglu, 2002; Acemoglu et al., 2016, 2012; Aghion et al., 2016; Hepburn et al., 2018; Johnstone et al., 2012, 2010; Popp, 2002). These different qualities of technologies provide the basis for the research articles, and will be explored in more depth in the next section.

1.4 Environmental Innovation and the Environment

From the previous remarks, it is evident that humanity faces substantial issues due to its impacts on the environment. Further, technology is considered to be a crucial factor in alleviating the environmental impacts caused by human activity. Innovation is the source of technological improvements when there is need of technological change. As technologies are developed and introduced with different intentions and there can be unintended side-effects, it is important to develop and deploy specific technologies. This section sets the stage for the subsequent chapters of this thesis that includes four research articles. The articles are empirical analyses on two different literature streams dealing with the concept of environmental innovation (EI) that bridges the topics of sustainability and technology. As noted in section 3.3.1, while technology implies all of the technologies applied with varying shares by a society, innovation enables technological change through improvements of technology by introducing novelty, either via the improvement of existent technologies, or the introduction of new technologies. This section consists of two main parts. The first part provides an introduction to the concept of EI, in order to better understand the specifics of the concept in the context of innovation economics and sustainability. Therefore, the concept will be fenced off against other definitions of innovation, followed by a comprehensive review of the main literature, and a discussion on the types and measurement of EI. Thus, the first part (4.1) serves to provide an overview of the connecting element of the four papers, and will offer a critical view of the research articles and their explanatory power. The second part (4.2) will introduce the papers with a focus on motivation, research questions, empirical design, main findings, and the contribution to the literature.

1.4.1 Environmental Innovation

Despite the previously discussed issues associated with technologies, there is consensus about the need for innovations that will maintain the highest possible levels of prosperity while complying with ecological limits (Barbieri et al., 2016; Canas et al., 2003; Haberl et al., 2011; Popp et al., 2010; UNEP, 2011). As environmental problems cannot be adequately addressed with current technologies (Popp et al., 2010), a technological change aimed at improving environmental quality and lowering environmental pressures is needed (Barbieri et al., 2016). Such environmental technological change is specifically targeted and supported by policy programs and initiatives such as the Climate & Energy Framework (European Commission, 2019), or the Circular Economy package (European Commission, 2015). In order to create an economic structure that has high resource efficiency and low greenhouse gas emissions, specific technologies are actively fostered to facilitate these shifts (European Commission, 2011).

1.4.1.1 Definition and Characteristics

The concept of EI was introduced to distinguish those innovations that contribute to a reduction of environmental pressure or to specified sustainability targets (Rennings, 2000). One of the most commonly accepted definitions is:

"[...] the production, assimilation or exploitation of a product, production process, service or management or business method that is novel to the organisation (developing or adopting it) and which results, throughout its life cycle, in a reduction of environmental risk, pollution and other negative impacts of resources use (including energy use) compared to relevant alternatives." (Kemp and Pearson, 2007, p. 7)

However, this is a rather general definition that does not take into account the relevance of economic benefits derived from such innovations. Ekins (2010) distinguishes the term ´eco-innovation´ as a subcategory of EI.[20] Whereas EI concerns environmental benefits only, eco-innovation is expected to simultaneously improve economic performance (Ekins, 2010), as eco-innovation has been defined as *"... a change in economic activities that improves both the economic performance and the environmental performance of society"* (Huppes et al., 2008, p. 29). According to Schiederig et al. (2011), the notions of 'eco-innovation', 'green innovation', and 'environmental innovation' are generally used synonymously in the literature, whereas the term 'sustainable innovation' tends to include a social dimension.

The concept of EI does not exclusively refer to technological innovations. Rennings (2000) distinguishes between technological, organizational, social, and institutional innovation. Technological innovations include both curative measures, such as soil decontamination, and preventive measures like end-of-pipe technologies (Rennings, 2000). Organizational changes refer to, for example, environmental management systems such as EMAS (Eco-Management and Audit Scheme) (Barbieri et al., 2016; Rennings, 2000). Social innovation concerns social changes (Cajaiba-Santana, 2014), for example, concerning consumption patterns (Rennings, 2000). Lastly, institutional innovations concern both local decision structures as well as global governance (Rennings, 2000). Such institutional measures are of crucial importance to successful governance of resources and ecosystems (Gerber et al., 2009). Thus, the concept of institutional innovation is essential for the concept of EI to be meaningful, as reductions 'throughout its life cycle' may only be provided by technologies when issues such as rebound effects, leakage, cost-shifting, or scale effects are considered and addressed (van den Bergh et al., 2011).

Some peculiarities of EI are worth stressing. The concept links innovation to environmental concerns, and is at the borderline of environmental economics and innovation economics (Rennings, 2000). Thus, EI suffers from the so-called double externality problem (Rennings, 2000) or even a 'triple externality problem' (van den Bergh et al., 2011). 'Double externality' refers to the presence of both a knowledge and an environmental externality (van den Bergh et al., 2011). Research and development (R&D) efforts are associated with knowledge spillovers, that is, some of the knowledge gained spills over to other actors who did not participate in the R&D but reap benefits from it (Rennings, 2000). In the diffusion phase, positive spillovers from the product or service occur as fewer external costs (environmental damage) are generated (Rennings, 2000). Hence, this 'double externality' leads to a substantially reduced incentive for

[20] Note that while Kemp and Pearson (2007) formulated this as the above given definition for eco-innovation, they did not distinguish between the terms environmental innovation and eco-innovation.

firms to be environmentally innovative, that is, their actions are below the socially optimal level. This situation may become even more severe due to increasing returns to scale that lead to lock-ins (Arthur, 1989), and could be considered a negative externality (Gerlagh and Hofkes, 2002), thereby resulting in a 'triple externality problem' (van den Bergh et al., 2011). These externalities make it particularly important that the regulatory framework and environmental policy facilitate the development and deployment of EI (Rennings, 2000). Environmental regulation influences the decisions of both producers and consumers and thus alters the demand and sector structure of an economy (van den Bergh et al., 2011). Furthermore, to reach sufficient levels of EI and achieve stated environmental goals both environmental and innovation policy is required. Supporting the introduction of green technologies by means of innovation policy such as subsidization can lead to an increased supply of energy, for instance. In the absence of environmental regulatory policies, however, this can result in a decreasing price of energy that may stimulate increased utilization, not only of renewable energy, but also non-renewable energy sources (van den Bergh et al., 2011). The opposite case of there being environmental regulation in the absence of innovation policy can bias selection pressure, as currently more mature and cost-effective technologies will be favoured and incrementally developed further, potentially leading to lock-ins of undesirable technologies (van den Bergh et al., 2011). Hence, policy measures to facilitate the right speed of innovation and maintain, at least for some time, a certain level of technological diversity so as to avoid early lock-ins are crucially important to the emergence and effectiveness of EI. In this sense, as Rennings (2000) emphasizes, the joint performance of technological, organizational, social, and institutional innovation is of central importance.

1.4.1.2 Literature Review

The literature on EI revolves around three main topics that are directly related to the peculiarities discussed above. These topics encompass the determinants of EI, its economic effects, and its environmental effects (Barbieri et al., 2016).[21] The relevance of each topic corresponds to the peculiarities of the concept. The determinants of EI are of crucial relevance, as EI development can suffer from a double or triple externality problem and, moreover, EI may demand a different knowledge basis than other innovations (De Marchi, 2012; De Marchi and Grandinetti, 2013). Hence, analysis of the determinants is crucial to better understand how

[21] Barbieri et al. (2016) distinguish as a fourth literature stream the policy inducement mechanism, which, however, we subsume as a subtopic of the determinants.

EI can be fostered. The economic effects of EI are of relevance not the least due to the environmental externality. For a firm, the economic benefits of innovation are crucial for it to be worthwhile. However, environmental innovations may not necessarily coincide with economic benefits, as some environmentally favourable measures, such as end-of-pipe technologies, may not influence market valuation of the product, leading to cost increases for the firm. As such innovation would adversely affect the firm's economic performance, the firm will likely not engage in it, even though doing so would be socially desirable given the environmental externality. Understanding the concurrence or contrariness of economic and environmental benefits is thus key to knowing how much policy support is needed. Lastly, the environmental effects of EI are of fundamental importance given that EI is intended to achieve certain environmental goals. Hence, understanding which technologies improve which environmental conditions and how technology development is related to technology effects is of utmost importance in justifying and guiding political pursuit of EI. This is particularly relevant due to the holistic nature of technological change emphasized in previous sections. In the following, the literature on each of these three dimensions (see Barbieri et al., 2016) will be reviewed. First, the literature on the determinants of EI will be discussed, followed by the economic effects, and lastly the literature on environmental effects.

As for the determinants, several elements are known to jointly stimulate firms´ adoption of EI,[22] including market-pull, technology-push, firm-specific, and regulatory factors (Barbieri et al., 2016). Market factors include both current and expected economic performance and demand for products, and are generally acknowledged to influence firms` choices (e.g., Horbach et al., 2012). Technology factors have been confirmed to be as important as market conditions in stimulating EI adoption. A firms' technological capabilities are, of course, crucial (Horbach, 2016) and these depend on the firms´ knowledge-capital endowment (Barbieri et al., 2016), which can be increased by technological activity and, in turn, improve absorptive capacities (Fisher-Vanden et al., 2006). The relevance of organizational capabilities and innovation should not be overlooked (Barbieri et al., 2016). For example, environmental management systems (EMS)[23] are considered to have a positive effect on EI adoption (e.g., Horbach, 2008), although

[22] In the following, it is chiefly spoken of EI adoption. However, developing and adopting EI can be two distinct events, which however both are considered similarly, as in the definition by Kemp and Pearson (2007). For development of EI, the knowledge externality is critical, whereas it is irrelevant for adoption. Adoption of an already present technology depends on incentives and technological capabilities. In empirical work, it can be hard to distinguish between development and adoption. While patent data capture development, survey data such as the Community Innovation Survey (CIS) may not allow clearly distinguishing between innovations that are new to the market and those that are new to the firm.

[23] Such as EMAS or the ISO standard.

the causal relationship remains unclear (Ziegler and Seijas Nogareda, 2009) as prior EI adoption can increase the likelihood of EMS adoption, as well as EMS facilitating the adoption of EI. In this context, building technological capabilities is highly important as the time of having adopted EMS positively affects innovativeness (Inoue et al., 2013). Firm-specific factors such as sector, size, location, or age also influence the adoption of EI (Barbieri et al., 2016; Horbach, 2016). Informational sources related to technological capabilities have been shown to affect EI (Cainelli et al., 2012; Horbach, 2016) and are at least somewhat affected by firm characteristics, such as membership in a business group. Lastly, regulation, the result of which has been labelled the 'regulatory push-pull effect' (Rennings, 2000), is crucial as regulatory measures influence both the supply side and the demand side (Barbieri et al., 2016). Regulatory incentives can affect any stage of an innovation process, from development to diffusion (Popp, 2005), with both current as well as expected policy measures having an influence (Carrión-Flores and Innes, 2010). However, some evidence points to the relevance of firms' EI despite the presence of weak policy stimulus (Ghisetti and Quatraro, 2013). The policy inducement mechanism suggested by Porter and van der Linde (1995) poses that environmental regulation may lead firms to innovate and thus enhance their competitiveness. The prevalent literature on this 'Porter hypothesis' finds that economic instruments are more beneficial than regulatory mechanisms in this context, as regulatory mechanisms may not push firms to surpass obligatory standards whereas innovation can reduce firms´ compliance costs (Barbieri et al., 2016). Indeed, EI policy should be designed to avoid suboptimal lock-ins and provide instruments suitable for different phases of the innovation process (Barbieri et al., 2016). For instance, it has been shown that while demand factors are key in the initial phase of EI, the magnitude of investment depends on factors such as cost savings and regulation (Kesidou and Demirel, 2012).

With respect to the economic effects, the effects of EI on short-term profitability could be different from its long-term effects on performance (Porter and van der Linde, 1995). Theoretical work by Faucheux and Nicolaï (1998) proposes that with appropriate governance, 'win-win strategies' concerning EI are possible. Similarly, Mazzanti and Zoboli (2009) point out that EI can improve both economic and environmental performance. Empirically, evidence of the effects on firm performance is mixed; some studies find economic benefits (Cheng et al., 2014; Lanoie et al., 2011), whereas others find EI to perform worse than regular innovations (Marin, 2014) or have heterogenous effects, depending on the type of EI under consideration (Ghisetti and Rennings, 2014). Concerning the 'job creation potential of EI' (Barbieri et al., 2016), Horbach (2010) finds a particularly large employment effect for EI, while Horbach and Rennings (2013) show that employment effects vary between different types of EI.

Lastly, the environmental effects are of utmost importance as alleviating environmental problems is the primary target of EI. Technological change toward more environmentally compatible technologies is of pivotal importance in achieving environmental sustainability (Jaffe et al., 2002; Popp et al., 2010). According to Barbieri et al. (2016), there are several mechanisms through which EI can affect environmental performance. First, green technological change can intensify the effects of other key variables (Barbieri et al., 2016). For example, innovation may have an impact on labour productivity, which, in turn, may affect environmental performance (Mazzanti and Zoboli, 2009). Second, it is possible that there will be spatial spillovers to neighbouring areas and regions (Barbieri et al., 2016). Costantini et al. (2013) show that both innovation and environmental spillovers[24] drive regional and sector-specific environmental outcomes. Third, sectoral spillovers can play a crucial role (Barbieri et al., 2016). Interregional spillovers within a sector are highly relevant (Costantini et al., 2013), but innovation decisions also are dependent on emission abatement efforts by other sectors (Corradini et al., 2014). The above-mentioned papers, however, do not explicitly analyse the effects of EI on environmental outcomes. Studies explicitly analysing the effects of EI primarily focus on pollution measures. Sectoral analysis finds an environmentally favourable effect of EI. Carrión-Flores and Innes (2010) find for US manufacturing industries between 1989 and 2004 that EI reduced emissions. Ghisetti and Quatraro (2017) find positive environmental effects on the environmental performance of regions-sectors in Italy, while Costantini et al. (2017) observe similar effects on manufacturing sectors in European countries. Similarly, Georgatzi et al. (2020) find such effect of green technologies on emissions in the transport sectors of 12 European countries between 1994 and 2014. Wurlod and Noailly (2018) find that green innovation contributed to reductions of energy intensity in the industrial sectors of OECD countries between 1975 and 2005. Studies at the regional level have more inconclusive results. Zhang et al. (2017) analyse Chinese provinces and find that EI measures reduce CO_2 per capita, whereas Wang et al. (2012), analysing total emissions in Chinese provinces, find no effect of innovation in fossil-related technologies but some effect of carbon-free energy technologies. Weina et al. (2016) observe, with regard to Italian regions between 1990 and 2010, that EI does contribute to improved environmental performance but not to reductions of absolute environmental impact.

[24] Proxied by the environmental performance of the same sector in other regions (Costantini et al., 2013).

1.4.1.3 Typologies and Measurement

Before discussing the empirical papers that are the body of this dissertation, a short review of the typology and measurement of EI is provided. Typologies are relevant as it is necessary to know what is being focused on and to what degree it is being analysed, that is, is a holistic or narrow scope of EI adopted, and is it rather development or adoption of innovations being analysed. Moreover, results can be sensitive to choice of indicators, with each type of measurement having advantages and disadvantages. Therefore, some suggestions concerning how to categorize EI will be discussed first, followed by a short presentation of possible EI measures.

Kemp and Pearson (2007) propose a typology for EI that distinguishes between four areas. Environmental technologies include, for instance, pollution control technologies, cleaner process technologies, and green energy technologies. Organisational innovation refers to environmental management systems and chain management. Product and service innovation includes new or environmentally improved products and services, such as eco-houses or environmental services. Green system innovations consist of alternative systems of production and consumption that are environmentally beneficial compared with existing systems, for example, biological agriculture or renewables-based energy systems. Frondel et al. (2007) emphasize process innovations, which largely correspond to what Kemp and Pearson (2007) term environmental technologies, to include distinctively end-of-pipe technologies and cleaner production technologies. EI has been categorized in other ways, too, for example, between curative and preventive (Rennings, 2000), or more specific classifications of green technologies such as energy efficiency improvements, dematerialization, recycling, pollution prevention, or renewable energies (Horbach et al., 2012; van den Bergh et al., 2011).

Different layers of indicators are useful in measuring EI. Kemp (2010) distinguishes four different layers, namely, input measures, intermediate output measures, direct output measures, and indirect impact measures derived from aggregate data. Input measures include research and development (R&D) related indicators such as R&D personnel or expenditures. Intermediate output measures encompass publications and patents, albeit these measure inventions rather than innovations. Direct output measures concern information on the number of innovations and related indicators such as data on sales. Indirect impact measures that can be derived from aggregate data include changes in environmental performance, such as resource efficiency. Each method and indicator has advantages and shortcomings (Kemp, 2010). Most studies, however, employ survey or patent data (Barbieri et al., 2016). Patent data is scrutinized with efforts to mitigate major issues, such as differing propensities to patent or value differences (Johnstone et al., 2010). Nevertheless, there are limits to this approach, such as overlooking nonpatentable innovations or accounting strategic patents, a restriction to technological innovation (Barbieri et al., 2016), and limited information on diffusion of the innovation (Kemp, 2010). In contrast, the wide availability and richness of detail make patent data very attractive (Haščič and Migotto, 2015). Survey data, such as the Community Innovation Survey (CIS), overcome some of these issues due to containing direct information on innovation impact at the firm level, yet may suffer from issues generally common to survey data, as well as more limited data availability and the consequent limitations for scientific analysis (Mairesse and Mohnen, 2010).

1.4.2 An Overview of the Dissertation Papers

In this section, an outlook on the following chapters of this dissertation is provided. An overview of the four studies along main characteristics is provided in Table 2. All of the papers are concerned with the concept of environmental innovation; however, different literature streams concerning EI are addressed. The first article (chapter 2) contributes to the literature on the determinants of EI, specifically the role of institutional factors for EI related to material use and carbon dioxide emissions. The second article (chapter 3) is concerned with the relevance of EI for reducing carbon dioxide emissions, which is the most frequently considered environmental indicator of highest policy relevance. The third and fourth article focus on the role of EI in the context of resource use, a previously unappreciated dimension in the literature on EI. The third article (chapter 4) sets the scene to establish this linkage both theoretically and empirically by establishing and operationalising EI categories relevant to material use, and analysing the effects of EI on total resource use. The fourth article (chapter 5) zooms in on the specific material groups of biomass and fossil fuels, which are of major importance to human societies.

Table 2: Overview of the dissertation papers by main characteristics

Chapter	Title	EI literature stream	EI data	Dep. Var.	Subject of analysis	Temporal scope
2	Do European Firms Obey the Rules? Environmental Innovativeness in Light of Institutional Frameworks	Determinants	Survey data	EI adoption, reducing CO_2 and material use	Firms	2008 and 2014
3	The Impact of Environmental Innovation on Carbon Dioxide Emissions	Environmental effects	Patent data	CO_2 emissions	Countries	1992 to 2014
4	About the Relationship Between Green Technology and Material Usage	Environmental effects	Patent data	Total resource use	Countries	1990 to 2012
5	Natural Resources and Technology - on the Mitigating Effect of Green Tech	Environmental effects	Patent data	Biomass and fossil use	Countries	1990 to 2012

Before introducing the individual chapters, it is worth recalling the EI data utilized (see 4.1.3). The first article (chapter 2) utilizes survey data. Thus, the definition of EI is holistic as not only technological, but also e.g., organizational innovations with environmental benefits are considered. Further, the understanding of innovation in the CIS data encompasses both the original development of innovations and the adoption of an externally introduced innovation by the firm.[25] Thus, within the CIS data, EI is not distinguished based on the type of innovation (e.g., technological or organizational) or the creation of genuine novelty (both development and adoption of external innovation are counted) but solely on the type of environmental impact that the innovation has, regardless of whether such is the primary objective or a ´side-effect´. Consequently, while the EI data used in chapter 2 is appropriate for analysing firms´ contribution to reducing specific environmental impacts via innovation, they contain restricted information on the nature of these developments and their contribution to genuine technological progress. The second, third, and fourth article (chapters 3 to 5) use patent data, and distinguish EI by definition of specific technological classes. Patent data are restricted to technological innovations only (Oltra et al., 2010). Moreover, for an invention to be patentable, genuine novelty is required, such that the mere adoption of an innovation by another firm is not

[25] That is, innovations that are new to the firm, but not to the market, constitute innovations within the CIS.

considered.[26] Thus, EI is classified based solely on the patents´ assignment to a particular technological field, not as above on specific environmental effects. Hence, the EI data used in chapters 3 to 5 well capture technology development in areas classified as EI, and thus actual technological progress. On the flipside, there is no direct link to the diffusion and environmental effects of these technological developments.[27] In short, patent measures are intermediate output measures (see Kemp, 2010), whereas the utilized survey data corresponds more closely to actual innovative output.

1.4.2.1 Do European Firms Obey the Rules? Environmental Innovativeness in Light of Institutional Frameworks

This paper studies the relevance of institutional quality for EI adoption by European firms. It is motivated by the crucial importance of EI adoption by firms, and the potential role that institutional factors can play in facilitating it. To better understand the effects of institutions on EI is both relevant for the literature on the determinants of EI, and for the policy relevance of institutional factors in the pursuit of green technological change. The paper contributes to the literature on innovation and institutional economics.

Due to its emphasis on firms' decisions, the paper utilizes survey data, specifically the Community Innovation Survey (CIS). Two independent survey waves are utilized due to their provision of information on firms´ EI activity: the 2006-2008 wave (CIS 08) and the 2012-2014 wave (CIS 2014). The firm-level information about firm characteristics and their EI from the CIS is combined with data on institutional factors at the national level. The institutional data distinguish between formal and informal institutions considered to encompass environmentally relevant institutional factors. Thus, the paper spans two distinct samples of several thousand European firms from 12 countries each. This data structure is the most important limitation of this study, for two reasons. First, due to the cross-sectional nature of the data, it is difficult to determine the direction of causality. Second, as the effects of institutions are examined at the national level, there are few observations on which these relationships can be investigated. The paper focuses specifically on EI adoption related to reduction of material use versus reduction of carbon dioxide emissions. The research question concerns the effect of the institutional measures on EI adoption, and the relations between the effects of the different institutional

[26] Nevertheless, in constructing patent-based measures, such diffusion dynamics are often intended to be captured.
[27] This necessitates studies analysing the environmental effects of technology development measured by patents.

dimensions, the effect on the different EI types, and whether these relations and effects are different between the two samples.

The analysis reveals some interesting findings by making use of both probit models and a two-step procedure suggested by methodological literature. In the first sample, CIS 2008, the effect of formal institutions is similar for both EI types. In the second sample, CIS 2014, formal institutions are substantially more important for EI in regard to emission reduction than for material use reduction. Informal institutions gained in relative importance for the adoption of material use reduction innovation. Generally, informal institutions are more closely related to the adoption of EI than are formal institutions. However, the results need to be viewed with some caution, given the few countries in the dataset, and because substantial differences in EI adoption between countries cannot be sufficiently related to the institutional variables under consideration.

The main contribution of the paper concerns the deployment of two CIS waves, and the matching of EI types with environmentally relevant institutional factors. The paper enhances our understanding of EI differences between European countries that persist beyond firm-level characteristics. Also, two substantially different types of EI were analysed and it was shown that not only are there different institutional impacts generally, but that these differences may evolve over time. This provides an important leverage point for further investigation of firms' EI adoption behaviour.

1.4.2.2 The Impact of Environmental Innovation on Carbon Dioxide Emissions

Motivated by the relevance of carbon dioxide emissions, the political pursuit of EI, and its theoretical uniqueness, this paper studies EI`s impact on carbon dioxide emissions at the national level. The paper contributes to the literature on the environmental effects of EI, the determinants of carbon dioxide emissions, and provides relevant evidence as to whether it makes sense to politically pursue EI.

Due to being interested in analysing the impacts at the national level over time, patent data on EI are employed. The paper utilizes yearly patent counts of EI patents classified based on official search strategies provided by the World Intellectual Property Organization (WIPO) and the OECD. The study spans the period of 1992 to 2014 for 27 EU countries. It focuses specifically on the effect of green innovation on territorial carbon dioxide emissions. The focus on domestic innovation and territorial emissions is an important limitation of the analysis, as upstream emission requirements as well as foreign technology development are not specifically taken into account. Testing the validity of the findings further, accounting specifically for spatial features of technology development, and using CO_2 measures that account for upstream requirements, is a natural extension of this work. The research goals in this study are to examine whether EI exerts an effect on carbon dioxide emissions, to discover whether this effect is unique to EI, and to provide insights into country heterogeneity with respect to the impacts of EI.

The analysis employs dynamic panel methods. The main finding is that, indeed, EI contributes to reductions in carbon dioxide emissions. This effect is found to be distinct from general innovation, which is not found to exert a significant effect. The crucial importance of energy consumption and energy composition is confirmed by the analysis, given large effects of both energy consumption and the share of renewable energy in the energy mix. A further contribution of the paper is its analysis of the role that country specificities play in the relationship between EI and carbon dioxide emissions. An interesting finding is that the effect of EI is weaker in less developed Eastern European economies than in developed Western European economies, which may be because Eastern European countries, which tend to be `catch-up` countries (Gräbner et al., 2018), might be less dependent on domestic innovation. Interestingly, however, excluding countries based on their domestic fossil industry instead of their economic development leads to an even stronger effect of EI. This effect occurs even though the excluded countries again all qualify as catch-up countries. This implies that the effect of EI may be particularly weak in countries with a strong domestic fossil industry. This finding is in accord with the recent study by Stevens (2019) showing that a strong domestic fossil industry has a negative impact on environmental regulation. Therefore, institutional aspects seem to be important for technology effects. It was also found that the countries with both the largest and smallest estimated effects of EI are Eastern European countries, indicating that less developed economies have a higher level of heterogeneity concerning technology effects.

The paper makes two distinct main contributions. First, it contributes to the literature on the environmental effects of EI by being the first cross-country study on carbon dioxide emissions that does not take a sectoral, but national, focus. Second, the findings on country heterogeneity with respect to EI contribute to the discussion on both developmental and institutional economics, as it is shown that these are very relevant when it comes to the environmental effects of green technologies.

1.4.2.3 About the Relationship Between Green Technology and Material Usage

This study was motivated by the fact that most studies on the environmental effects of EI focus on air pollution.[28] Material use indicators, however, are considered to be more holistic measures of environmental impact; they capture societies´ undeniable dependence on the environment, instead of isolating the effects of emissions only.[29] Furthermore, while emissions are negative externalities, resources are both crucial inputs to production and also directly related to environmental pressures. At the policy level, reduction of material inputs is considered important for reasons of both sustainability and competitiveness. Hence, this paper studies the effects of EI on total material use in EU countries. This work contributes to the literature on the environmental effects of EI, the determinants of resource use, and provides evidence of policy relevance concerning the implications of EI for sustainability and competitiveness.

Given the paper's interest in analysing effects at the national level over time, patent data on EI are employed. Patent stocks on EI were generated to account for the diffusion and depreciation of technologies. The WIPO and OECD EI patent search strategies were again utilized. However, given the specificities of material use, more refined EI categories were defined. Five relevant areas of EI beyond a general EI classification were constructed, namely, EI related to energy efficiency, alternative energy production, the production or processing of goods, transportation, and recycling and reuse. These areas capture potentially different relationships between EI and material use. The study spans the period of 1990 to 2012 for 27 EU countries. It focuses on the effects of the abovementioned EI measures on two distinct material indicators: Direct Material Input (DMI) and Raw Material Input (RMI). Both indicators capture all materials entering the economy. DMI accounts for imported materials by their mass; RMI accounts for imported materials by including material requirements generated upstream, meaning that issues like outsourcing are taken into account. Limitations of this study involve construction of the innovation variables and the material use indicators. First, spatial features of technology development are not specifically accounted for, which would be a valuable contribution of future studies. Second, the focus on total resource use makes it impossible to observe distinct effects on individual material groups, which can be of differing economic and environmental significance. The main question is whether EI reduces material use at the

[28] An exception is the study by Wurlod and Noailly (2018), which focuses on energy intensity, a measure of environmental performance (not pressure or impact), within sectors.
[29] For example, by carbon capture and storage technologies.

national level, whether differences between EI areas exist, and whether there are observable differences between DMI and RMI.

The analysis employs dynamic panel methods. A main finding is that significant reductions of material use are found for only two specific areas of EI: recycling and reuse, and energy efficiency. Other categories of EI, including overall EI, do not exert significant effects, nor does a measure of general innovation. The effects of EI are similar for both material use indicators. Hence, concerning the environmental effects of EI in the context of resources, the findings point to heterogenous effects between technology areas. The findings on further determinants, such as GDP and economic structure, in relation to the material use indicators, have implications for the literature on decoupling. GDP raises RMI more strongly than DMI. At the same time, increases in the industry sector's share increase DMI in a more pronounced way. These findings confirm the notion that European countries profit from outsourcing material-intensive activities, which can be captured by taking upstream requirements into account via the RMI indicator.

The paper makes three main contributions, two of which are to the literature on the environmental effects of EI. First, the linkage between EI and resource use is established, something not done in previous literature. Second, relevant areas of EI were distinguished and operationalised, and it was shown that different EI technology areas have different implications for resource use. Third, utilizing both RMI and DMI confirmed that developed economies profit from outsourcing, and that decoupling successes are less substantial when accounting for upstream flows.

1.4.2.4 Natural Resources and Technology - on the Mitigating Effect of Green Tech

In light of the discovery of the link between EI and resource use discussed above, it is vital to disentangle the effect of EI on different material categories, both from a sustainability and socioeconomic perspective, as different material groups are characterized in different ways. This concerns, for example, the substitutability of materials. Fossil materials may, in principle, be substituted. Biomass, on the contrary, is inevitably used due to nutritional needs. This paper focussed on biomass and fossil materials specifically, for the following reasons. First, historically, it was the shift from biomass to fossil materials that led to societal development in the Anthropocene and enabled the large-scale utilization of other materials like metals and non-metallic minerals. Second, in terms of providing nutrition and energy, the two material groups jointly constitute the foundation of modern society. Third, both material groups are intimately related with sustainability issues. Lastly, a shift back again from fossils to biomass has been discussed by scholars as the next fundamental change since the Industrial Revolution. Hence, in this paper the effects of EI on biomass and fossil material use in EU countries are studied. The paper contributes to the literature on the environmental effects of EI, the determinants of biomass and fossil use, and the current role of EI in the reconfiguration of social metabolism.

Once again, patent stocks for different categories of EI are constructed. Also, the time-span is identical, covering 1990 to 2012 for the same 27 EU countries, and both DMI and RMI are again employed. Main limitations again involve the choice of innovation variables and material use indicators. As noted previously, accounting for spatial features of technology development will be a natural extension. Further, at least in the case of biomass material use, the material category still includes a substantial level of heterogeneity. The main question concerns whether EI influences the utilization of biomass and/or fossil materials, which EI categories prove relevant for which material type, and whether there are observable differences between DMI and RMI. The analysis again employs dynamic panel methods.

There are several interesting findings. First, with respect to biomass material use, no significant technology effect is found; this holds both for RMI and DMI. Second, neither is there any significant technology effect found for fossil materials - for the whole sample period (1990-2012). However, it is discovered that the composition of fossil use in European countries evolved over time, and at a rapid pace in the early 1990s. More specifically, in the early 1990s there was a substantial substitution of oil and natural gas for coal. This substitution effect is relevant, as no control variable captures this substitution, although oil and gas imply the same amounts of energy at substantially lower weight. This could distort information contained in the respective indicators. When excluding the years before 1996, the results changed and some categories of EI showed significant effects on fossil use. These effects were found exclusively for RMI, not for DMI. The two categories for which effects were found are recycling and reuse, and the production or processing of goods. The effects of recycling and reuse were more pronounced. Similar to the findings in chapter 3, the estimated effects of EI are substantially larger when countries with a strong domestic fossil industry are excluded. Given that both the environmental and innovation indicator were different in this study than in the one discussed in chapter 3, these results point to the relevancy of country specificities. Another finding is the relevance of net energy imports as a determinant of fossil material use. Net energy imports capture dependence on foreign energy and, given the findings about the substitution of coal in European countries, partly capture substitution of natural gas and oil for coal. The significance throughout both the full (1990-2012) and restricted (1996-2012) sample, as well as for both

RMI and DMI, points to the importance of capturing energy import effects when analysing fossil use.

The paper makes two main contributions. First, the effects of EI on biomass and fossil, as core material categories, were analysed and the relevancy of different types of EI was shown. Second, the relevance of accounting for substitutional dynamics within fossil material use was shown, including the introduction of a previously unappreciated control variable, namely, energy imports.

1.5 Conclusion

Aligning human requirements with environmental restrictions calls for the best possible utilization of technology so as to secure environmental quality while at the same time providing the highest possible levels of prosperity to human societies (Barbieri et al., 2016; Popp et al., 2010). The pursuit of this goal led to the concept of environmental innovation (EI), meaning the development and deployment of ‘green technologies’ that are intended to simultaneously secure prosperity and environmental quality. Indeed, political programmes of all stripes often refer to the potential for ‘green technological change’ to secure future viability of global human development (Altenburg and Assmann, 2017; European Commission, 2015; OECD, 2011; UNEP, 2011; United Nations, 2015).

The present thesis contributes to this growing body of literature with studies on both the causes of EI and its environmental effects. The results of the studies indicate that, indeed, EI can reduce both inputs to production, like material use, and undesired production outputs, such as carbon dioxide emissions (chapters 3 to 5). The results show that different technological fields have different environmental effects (chapters 4 and 5), indicating that technological change needs to be steered in the right direction for specific outcomes to be achieved. Yet, at the same time, relevant EI categories have not yet reduced environmental pressure. The results also showed that besides reductions owed to green technologies, economic growth often surpasses efficiency improvements, such that actual environmental pressure continues to rise. This is particularly daunting as the analysed countries are developed economies whose economic growth had been hypothesized to contribute to reduced environmental pressure (Stern, 2004). At the global level, as the evidence in section 2.3.2 shows, this rise of environmental impact continues unabated. Another important finding concerns the heterogeneity of environmental effects of EI between countries (chapters 3 and 5). These findings are in line with the evidence that country specificities, that is, institutions, influence the introduction of EI by European firms (chapter

2). Hence, there are three main conclusions that can be drawn. First, EI has specific environmental effects and should be explicitly pursued, but the heterogeneity of EI categories and holistic impacts must be appropriately taken into account. Second, societal characteristics, that is, institutional factors, seem to mediate the effectiveness of technology. Third, so far, and this seems unlikely to change within the next decades, technological progress alone will not suffice to avoid global environmental collapse.

It has been argued that the transition of less developed economies toward an industrial lifestyle constituted the basis of the Great Acceleration (Fischer-Kowalski et al., 2014; Haberl et al., 2011), and still continues. Emerging economies, such as China and India, are rapidly catching-up with high rates of economic growth (Fu et al., 2011), and have been the drivers behind recent acceleration of global growth in resource use (Krausmann et al., 2018). Given the limited success of decoupling in developed economies (Haberl et al., 2011; Parrique et al., 2019), the shift to an industrial lifestyle by populous countries such as China and India will inevitably require larger and larger amounts of resources and energy (Haberl et al., 2011). To align these developments with environmental restrictions, a circular economy - an economy with closed material loops and indefinite recycling - has been considered (Cullen, 2017; European Commission, 2015). Such visions, however, require enormous amounts of energy that are economically (Murphy and Hall, 2011) and environmentally compatible (Ausubel, 1989). Although there may be sources of vast amounts of energy such as nuclear fusion, or thorium (Cooper et al., 2011), that could create a new energy regime alongside hydrogen as an energy carrier (Ausubel, 1989; Scott and Häfele, 1990), it remains uncertain whether such visions are practically feasible. Further, technology tends to be accompanied by unintended side-effects (Ausubel, 1989; Grunwald, 2018) that can have huge consequences, especially as humanity has entered a full world in which consequences directly emerge (Daly, 2005; Rosenberg, 1971).

Historically, technological progress and the resulting availability of cheap energy laid the foundations for rapid human development (Cordes, 2009; Murphy and Hall, 2011; Steffen et al., 2007). This human expansion, however, has generated a situation in which humanity undermines its own foundation (Schramski et al., 2015). In the coming decades, we will need to be very careful about how we choose and use technology. The goal will be to alleviate environmental pressures while securing prosperity for all, with a substantially reduced margin for error (Steffen et al., 2015); instead of fuelling further expansion of the human species. Beyond all economic constraints and dynamics, how we use technology, treat our environment and other living beings, and thus shape our future on this planet remains solely in our hands.

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Chapter 2

Do European Firms Obey the Rules? Environmental Innovativeness in Light of Institutional Frameworks

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Abstract

Based on institutional and innovation theory, we explore the relationship of institutional factors with two highly relevant and heterogenous types of environmental innovation, namely: the reduction of material use (Ecomat) and the reduction of carbon dioxide emissions (Ecoco). We utilize the 2008 and 2014 survey waves of the Community Innovation Survey (CIS). This allows us to explore two separate cross-sectional samples at different points in time. Each sample is drawn from twelve European Union countries, giving us a total of about 70,000 firms. We find that formal institutions more strongly influence Ecoco innovation, especially for the CIS 2014 sample. We find that informal institutions affect both innovation types similarly.

Keywords: Community Innovation Survey ® Environmental innovation ® Green technological change ® Institutions ® Probit models

JEL Classification: Q01; O31; Q55

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2.1 Introduction

Economic activity has led to considerable increases in environmental pressures. This relates both to resources, such as material and land use (Behrens, 2016; UNEP, 2016), and polluting emissions, such as carbon dioxide (Solomon et al., 2009). Innovations are a key force to mitigate the detrimental effects of production and consumption (Popp et al., 2010). Innovation, and associated technological change, can reduce environmental impact either due to general productivity gains and/or specific changes that reduce specific environmental impacts (Stern, 2004). Driven by the increasing importance of environmental issues, facilitating specific environmentally beneficial technologies is of central interest.

The European Union (EU) sets ambitious targets in order to motivate environmental policy in its member states (Deters, 2019). Resource efficiency is of pivotal interest for European policy (European Commission, 2008, 2010, 2011a, 2015), not only for environmental reason, but as a way to improve competitiveness in the marketplace. The reduction of emissions is also a focal point of environmental goals. The EU has targeted 2030 as the year in which 1990 emissions levels will be reduced by 40% (European Commission, 2019). The consensus is that eco-innovation is a fundamental aspect in achieving these goals, (European Commission, 2011b).

The strategies that firms develop when it comes to which specific innovations to introduce are dependent not only on firm characteristics, such as size or capabilities, but also on the socio-political surroundings a firm is faced with.

Environmental policy and institutional factors are of crucial importance for environmental innovative activity (EI), due to the limited appreciation of environmental benefits by the market (Horbach, 2016; Rennings, 2000). Both regulatory and normative institutional pressures have been shown to influence firms' decisions to be environmentally innovative (Berrone et al., 2013; Garrone et al., 2018; Liao, 2018). Besides similarities, different types of EI may be dependent upon different factors (Demirel and Kesidou, 2011; Frondel et al., 2007; Horbach et al., 2012), for example due to differences in the relationship between environmental and economic benefits originating from the innovation.

This paper contributes to the scant literature by explicitly analysing the role of institutional factors for EI (Berrone et al., 2013; Garrone et al., 2018; Liao, 2018), drawing upon the broader literature on the determinants of EI (Barbieri et al., 2016). We extend this literature by analysing how institutional pressures affect different types of process innovations dependent upon the environmental effect. Specifically, we focus on two types of EI related to material use and the emission of CO_2, both of which are of particular interest from a political perspective in Europe. We choose these two types because their defining characteristics are fundamentally different. Materials are inputs into the production function (O'Mahony and Timmer, 2009), such that reducing material use should not only provide environmental benefits but also save costs, thereby increasing the firm's competitiveness. Because CO_2 emissions are a negative externality, the reduction of these emissions does not directly benefit the firm. In fact, compliance may increase costs. Hence, we expect that institutional pressures affect these two EI types in vastly different ways. Another contribution of this paper concerns the data. We take both the cross-country dimension and the time dimension into account. Both the CIS 2008 and the CIS 2014 survey waves solicit information about EI. By using both waves, we are able to analyse how institutional effects may differ between samples.

The paper is structured as follows. Section 2 introduces a theoretical framework, laying the foundation for our investigation of the institutional environment. The data employed, with a particular focus on the institutional measures, will be introduced in Section 3. Section 4 explains the empirical procedure. Section 5 presents the results that are discussed in Section 6.

2.2 Theoretical Framework

Institutions are considered to be a central element of an innovation system, however, there are a variety of perceptions as to how they relate to each other (Edquist, 1997). Nelson (1993) focused on institutional actors: firms, research laboratories and universities. Lundvall (1992) introduced the notion of an *"institutional set-up"*. In this sense, institutions provide agents with guidelines for their actions, thereby making *"... it possible for economic systems to survive and act in an uncertain world"* (Lundvall, 1992, p. 10). Veblen (1919/2012) stated that *"...the institutional scheme is a matter of law and custom, politics and religion, taste and morals..."* (Veblen 1919/2012, p. 44). *"The rules of the game in a society..."* is the most widely used definition of institutions (North, 1990, p. 3). Hodgson (2006) considers institutions as *"...social rules that structure social interactions"* (Hodgson, 2006, p. 2). This wide range of definitions for institutions affect the analytic focus of various strands of literature. For example, some schools of thought focus on economic agents, while other schools focus on particular rules or the broader social context (Nelson, 2005).

General speaking, there is agreement that differences in institutional quality can explain differences in economic development between countries (Acemoglu and Robinson, 2012; De Soto, 2000; North, 1990). Recent empirical results confirm this assumption (Acemoglu et al., 2002; Hall and Jones, 1999; Kapás, 2019; Rodrik et al., 2004; Williamson, 2009). Results show, however, that it is the interaction between formal and informal institutions that is more important than institutional frameworks in general. Formal rules include political and legal constraints (e.g. constitutions), written contracts, codified standards, property rights, or regulations (Boettke and Coyne, 2009; de Soysa and Jütting, 2007; North, 1990; Williamson, 2009). Informal rules are uncodified constraints, which are *"…created, communicated and enforced outside of officially sanctioned channels"* (Helmke and Levitsky, 2004, p. 727). They manifest as norms, conventions, social customs, values, attitudes, or traditions (Boettke and Coyne, 2009; de Soysa and Jütting, 2007; North, 1990; Williamson, 2009). A critical distinction between formal and informal institutions is that formal institutions are considered to be "fast-moving", whereas informal institutions are considered to be "slow-moving" (Roland, 2004). Informal institutional change can be rooted in formal institutional change, or through the evolution of cultural norms (Helmke and Levitsky, 2004). According to a typology proposed by Helmke and Levitsky (2004), informal institutions interact with formal institutions in one of four ways: complementary, accommodating, competing, or substituting. When formal institutions are effective, informal institutions might play a complementary or accommodating role. However, if formal institutions are ineffective, informal institutions might substitute or compete with the formal institutional environment. Based on empirical results, Williamson (2009) defined four institutional categories: strong formal and strong informal institutions, weak formal and strong informal institutions, strong formal and weak informal institutions, and weak formal and weak informal institutions.

González-López (2011) pointed out that the interactions between institutions and innovation activity are manifold. Not only is it possible that innovations may change institutions, but institutions might either foster innovation, or be a barrier to innovation activity. High quality formal institutions appear to have a positive impact on innovation in general (Lee and Law, 2017; Tebaldi and Elmslie, 2013), and on innovation-intensive exports more specifically (Silve and Plekhanov, 2015). Strong informal institutions appear to complement formal institutions in supporting innovation development (Lee and Law, 2017). Moreover, strong informal institutions are found to be positively related with innovation cooperation (Geng and Huang, 2017; Srholec, 2015).

Firms are motivated to engage in environmentally innovative activities mostly by demand factors, cost savings, subsidies, and regulations (Borghesi et al., 2015; Cai and Li, 2018; da Silva Rabêlo and de Azevedo Melo, 2019; Del Río et al., 2017; Demirel and Kesidou, 2011; Díaz-García et al., 2015; Hojnik, 2017; Horbach, 2016, 2008; Horbach et al., 2012; Kesidou and Demirel, 2012). Regulations are found to be most effective in increasing eco-innovations in less innovative firms (Kesidou and Demirel, 2012), in impacting end-of-pipe pollution control technologies, as well as environmental R&D (Demirel and Kesidou, 2011). Horbach (2016), analysing regulatory push factors, found that present and future (expected) regulations are positively related to innovations intended to reduce CO_2 or other air pollution emissions. Similarly, a positive effect of subsidies was identified. Borghesi et al. (2015) found similar relations. Similarly, innovations intended to reduce SO_2 emissions are stimulated by present and anticipated regulations (Taylor et al., 2005). In the case of innovations aimed at reducing material and energy use, regulations were found less significant whereas cost savings were a more important motivation (Horbach, 2016). Van den Bergh (2013) suggested that only a combination of environmental regulations (aimed to reduce negative externalities) and innovation policy (aimed to boost innovation) is able to stimulate eco-innovations that address specific environmental issues. Verschuuren (2017) finds that the attitudes of stakeholders are key to successfully implementing requirements set by laws and regulations, emphasizing that social factors play a key role in compliance.

In our research we use the definition of institutions proposed by North (1990), namely *"rules of the game"*. To this end, we specifically focus on regulations (formal institutions), with special attention given to regulations dealing with environmental issues. We also focus on social values (informal institutions) that specifically relate to the importance of environmental quality. We expect that the introduction of EI in the areas of material use and CO_2 emissions will be positively impacted when institutions are of a high quality. Due to their characteristics and the related literature, we expect that formal institutions are particularly important in the case of emission EI.

2.3 Data

We analyse two separate samples of European firms drawn from different member states of the European Union. We collect firm-level information using two survey waves of the Community Innovation Survey (CIS), namely: the CIS 2008 (2006-08) and 2014 (2012-2014). Both survey waves asked firms to describe their environmental innovation activities (EI). As some firms did not answer relevant questions, we have available data from both survey waves for twelve countries. For the CIS 2008 wave, these include: Cyprus, Czech Republic, Germany, Estonia, Hungary, Ireland, Lithuania, Latvia, Portugal, Romania, and Slovakia. For the CIS 2014 wave, Ireland and Cyprus are not available, but Greece and Croatia join the sample. In total, we have

~46,000 firms from the CIS 2008 and ~24,000 firms from the CIS 2014. Thus, our sample covers countries at different stages of development, with a corresponding heterogeneity in institutional environments. Our sample includes both non-innovative and innovative firms. The innovative firms in our sample include both EI firms and firms engaged in other innovative activity.

We construct two dependent dichotomous variables capturing process innovations regarding specific environmental effects. First, whether a firm introduced an innovation that reduced material use (Ecomat), and second, whether a firm introduced an innovation designed to reduce its CO_2 emissions (Ecoco). We focus on these two EI types for several reasons. First, material use is a cost factor, whereas CO_2 tends to qualify as a negative externality. Second, material use is an input factor into production, whereas CO_2 is an undesired output of production activities. Third, material use captures a general set of inputs, whereas CO_2 is a very specific output and is a focal point of environmental policies. Focusing on these two distinct aspects of EI allows us to determine the impact of various types of institutional effects.

Table 1 lists the percentage of firms in each country that introduced an innovation designed to address environmental concerns. We divide the innovations into three categories: Ecomat, Ecoco, and any type of environmental innovation (EnvInno). We also differentiate between the CIS 2008 (08) and the CIS 2014 (14) survey waves.

Table 1: Percentage of firms that introduced different categories of innovation

Country	Ecomat 08	Ecoco 08	EnvInno 08	Ecomat 14	Ecoco 14	EnvInno 14
Bulgaria (BG)	11.61	6.00	23.66	9.88	8.97	20.38
Croatia (HR)	N.A.	N.A.	N.A.	26.05	27.70	51.58
Cyprus (CY)	6.84	5.37	15.82	N.A.	N.A.	N.A.
Czech (CZ)	20.41	14.45	48.50	27.33	34.64	60.91
Germany (DE)	36.88	33.48	63.16	30.18	47.65	62.27
Estonia (EE)	15.15	6.22	30.76	9.36	11.58	20.69
Greece (GR)	N.A.	N.A.	N.A.	22.94	29.60	55.08
Hungary (HU)	37.28	19.93	63.67	21.50	24.65	45.21

Table 1 continues

Ireland (IE)	24.00	26.99	50.08	N.A.	N.A.	N.A.
Lithuania (LT)	12.55	9.85	22.64	18.20	34.70	50.50
Latvia (LV)	9.70	7.82	23.98	19.88	27.04	48.11
Portugal (PT)	27.91	22.00	58.95	28.63	33.09	65.61
Romania (RO)	16.92	12.83	32.79	13.47	13.47	30.98
Slovakia (SK)	11.11	7.27	24.35	23.59	25.34	45.71

Our main explanatory variables are constructed to capture the difference between formal and informal institutions. To limit reverse causality concerns (see Garrone et al., 2018), all institution-related variables were measured either prior to, or at the latest, at the start of the timeframes under consideration. Table 2 specifies the various dates of the datasets used to establish these variables.

Table 2: Data used in the construction of the institutional variables

Institutional aspect	Data
Environmental regulatory stringency	Global Competitiveness Report 2003/4 (Data for 2003/4) and Global Competitiveness Index 4.0 2018 dataset (Data for 2009/10) (sources: World Economic Forum 2004, 2018)
Government effectiveness	The Worldwide Governance Indicators, 2017 Update (Data for 2003-5 and 2009-11) (source: World Bank)
Regulatory quality	The Worldwide Governance Indicators, 2017 Update (Data for 2003-5 and 2009-11) (source: World Bank)
Vote shares of green parties	Database of Political Institutions (Data for 2006 and 2012) (source: World Bank)
Vote shares of green and/or leftist parties	Database of Political Institutions (Data for 2006 and 2012) (source: World Bank)

To operationalize formal institutions, we use data from the World Economic Forum`s Global Competitiveness Reports (GCR), and data from the World Bank`s Worldwide Governance Indicators (WGI). From the GCR, we use the data on stringency of environmental regulations. More stringent environmental regulations should exert direct pressure on firms to improve their environmental performance. We apply the values from the GCR 2003-04[30] to our CIS 2008

[30] Note that for Cyprus we had to take the value from the GCR 2005-06, as there was no data for Cyprus in the 2003-04 report. However, these variables are rather slow moving, as can be confirmed when looking at the

data, and the reported values from the GCR 2009-10 to our CIS 2014 data. From the WGI, we use indicators on government effectiveness and regulatory quality. These indicators capture the general quality and enforcement mechanisms of the institutional environment, which is key for regulations to impact a firm's behaviour. We construct our variables using the reported values from 2003-05 and 2009-11, and apply these values to our CIS 2008 and 2014 data, respectively. All indicators were min-max-normalized to range between 0 and 1. To construct a single measure for the formal institutional environment, we ran an exploratory factor analysis based on principal component factoring. The factor analysis revealed that all variables load on the same underlying factor, yielding a standardized variable for formal institutions.

Because of the latent nature of social norms and values, the choice and measurement of an indicator to capture the informal institutional environment is quite demanding. Our interest in determining the degree of pressure a society brings to bear on firms to be environmentally friendly narrows our choices of indicators as well. After considering both the European Social Survey (ESS) and the European Values Study (EVS), we opted to use data from the Database of Political Institutions (DoPI). Using either the ESS or EVS surveys would have limited the number of observations.

The DoPI provides annual data displaying the most recent election results. We consider the latest election results as a revealed preference on the relevance of certain political and social goals. To construct two variables we first sum up the vote shares of parties that explicitly advocate green politics. We then sum up the vote shares of parties that lean towards green politics and the vote shares of leftist parties. Left-oriented individuals have been found to be characterised by more pro-environmental attitudes and tend to support environmental protection actions and policies (Davidovic et al., 2019; Dunlap, 1975; Neumayer, 2004). Larger shares of such voters in a community relate to the propensity for collective action to be undertaken and thus the exertion of normative pressure on firms (Berrone et al., 2013; Delmas and Toffel, 2004). We use the data for 2006 and 2012 from the DoPI,[31] and apply it to the CIS 2008 and 2014 data. Again, to construct a single measure we run an exploratory factor analysis. Our analysis reveals that both measures load on the same underlying factor, providing us with one standardized variable for informal institutions.

corresponding values for countries included in both reports. Hence, we consider this a good alternative to losing Cyprus as observation.

[31] The values in the DoPI for these years corresponded to elections that took place at least one year prior. It should be noted that assigning parties as leftist/green involves a certain level of uncertainty and imprecision. However, we consider the measurement to present a meaningful approximation of social values.

Interaction variables of both institutional dimensions are constructed by min-max-normalizing all institutional measures. The values for the formal and informal dimension are obtained by adding the three formal institutional dimensions together and dividing by three, and then adding the two informal institutional dimensions together and dividing by two. Thus, the minimum and maximum possible for both the formal and informal dimension are zero and one. In order to standardize the interaction variables, we multiply the formal and informal dimension.

In order to identify the effect of national-level institutions we need to account for the firm-level determinants involved in the introduction of EI (Horbach, 2016). Most strikingly, larger firms are more prone to engage in innovative activities and are more likely to have the needed resources. Therefore, we rely on information provided in the CIS surveys to control for firm size, and we are able to generate a continuous variable for firm size (Size).[32] The sectoral affiliation of a firm is also a relevant determinant, as the incentives and necessity to be environmentally innovative are heterogeneous across sectors. Hence, we include industry dummies at the most detailed level provided in the CIS data (Ind. dummies). Knowledge is more likely to flow from one firm to another if the firms belong to a business group. Hence, in order to capture knowledge inflows we control whether the firm is part of a business group (Group). Lastly, as we are measuring the impact of institutions at a national level, it is relevant whether the firm may be influenced by institutional pressures occurring in foreign markets that the firm has penetrated. Thus, we control whether the firm is internationally active (International). A full overview of variables employed in our analysis is provided in Table 3. We used the EnvInno variable only for descriptive statistics, and later for robustness checks. We did not use it for the main analysis of which results are reported.

Table 3: Description of the variables used in the analysis

Variable	Description
Ecomat	Binary variable accounting for the introduction of a process innovation reducing material use (“1”: Introduced innovation, “0”: Did not introduce innovation) (source: CIS)
Ecoco	Binary variable accounting for the introduction of a process innovation reducing carbon dioxide emissions (“1”: Introduced innovation, “0”: Did not introduce innovation) (source: CIS)
iForm	Formal institutional variable; standardized (mean = 0, SD = 1) (sources: see Table 2)

Table 3 continues

[32] For each size class, we assign the firm the middle value. For example, each firm belonging to size 10-50 employees, we assign 30. This firm size variable is logarithmized for inclusion into the model.

iInf	Informal institutional variable; standardized (mean = 0, SD = 1) (sources: see Table 2)
Group	Binary variable accounting for firm belonging to a business group ("0": Not part of a group, "1": Part of a group) (source: CIS)
International	Binary variable accounting for international activity of a firm ("0": Not internationally active, "1": Internationally active) (source: CIS)
Size	Continuous variable accounting for firm size (source: CIS)
Ind. dummies	Dummies accounting for the sector the firm is active in (source: CIS)

2.4 Model Specification

Given the binary nature of our dependent variables we apply non-linear probit models. For an EI type a firm either introduces an innovation (Y=1) or not (Y=0). We estimate the probability

$$Prob\ (Y = 1|x) = F(x, ß) \qquad (1)$$

with the vector x summarizing the explanatory variables, and the vector ß capturing the coefficients. The vector x includes the institutional variables, dummies for the firm belonging to a group and whether a firm is internationally active, dummies for each sector a firm may belong to, and the size variable (see Table 3). The *ß* parameters reflect the effect that changes in x have on the probability of innovation (Greene, 2012). We calculate marginal effects at the means (MEM), displaying the change in the probability for a change from the minimum to the maximum value of an explanatory variable. This is standard for dummy variables, yet we apply it to calculating the MEM of continuous variables as well. Since the outcomes of both EI types may be correlated leading to inconsistent estimates of the univariate probit model (Greene, 2012), we also ran the models using bivariate probit analysis that will be discussed as robustness checks (following Horbach, 2016).

While the utilization of such an approach is in line with recent similar work (Garrone et al., 2018), our interest in the effect of country-level determinants on firm behaviour causes some uncertainty for analysis. There is natural hierarchy with observations as the individual level (firm level) is nested within a higher level (countries) (Bryan and Jenkins, 2016). At the individual level our dataset contains thousands of observations, however, there are only twelve countries for each survey wave. This leads to uncertainty concerning the estimation of country effects (Bryan and Jenkins, 2016), which are our primary focus of interest. Hence, we complement our probit analysis described above in the robustness section by applying a two-step approach, as suggested by Bryan and Jenkins (2013). In the first step, we run the regular probit analysis including country dummies instead of the institutional variables. In a second step, we regress the country-fixed effect on the institutional variables using OLS.

2.5 Empirical Results

2.5.1 Main Results

Table 4 presents the estimation results based on the CIS 2008. We report three combinations of institutional variables for each EI type. Column 1 and 2 involve only the variable for formal institutions (Model 1). Better formal institutions are expected to positively affect the probability that firms introduce an EI. This hypothesis is confirmed, as the marginal effect at the mean (MEM) is positive and highly significant, both for Ecomat and Ecoco. According to our estimations, the probability that a firm will introduce an EI relating to material reduction is 12.89% higher in the country with the strongest formal institutions compared to the country with the weakest formal institutions, if all other variables are taken at their mean value. This difference is a little larger for CO_2 emissions, where the estimated difference amounts to 14.13%.

Table 4: Results of probit models for the CIS 2008

	(1)	(2)	(3)	(4)	(5)	(6)
Analysis type	Univariate Probit	Univariate Probit	Univariate Probit	Univariate Probit	Univariate Probit	Univariate Probit
Dep. Var.	Ecomat	Ecoco	Ecomat	Ecoco	Ecomat	Ecoco
Inst. Var.	Model 1	Model 1	Model 2	Model 2	Model 3	Model 3
iForm	.1289***	.1413***	.0558***	.0723***		
iInf			.1264***	.1204***		
iForm*iInf					.1525***	.1636***
Size	.1304***	.1279***	.1340***	.1316***	.1330***	.1299***
Group	.0376***	.0190***	.0433***	.0242***	.0451***	.0273***
International	.0422***	.0086**	.0438***	.0100***	.0461***	.0132***
Sectors	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	46190	46190	46190	46190	46190	46190

Notes to Table 4: *Marginal effects at the means are reported. Concerning dummy variables, the values report the change in probability for a discrete change of the dummy variable from 0 to 1.*
*For continuous variables (Size, iForm, iInf, iForm*iInf) we report the change in probability when varying the concerned variable from the minimum to the maximum value.*
, **, * denote significances of the marginal effects at the 10%, 5%, and 1% level, respectively.*
Ind. Dummies (Sectors), at the most detailed level provided in the CIS data, are included but not reported. The constant is not reported. Robust standard errors were used.

This picture changes when including the informal institutional variable (Model 2) as the effect of formal institutions is significantly reduced to 5.6% for materials and 7.2% for CO_2, respectively. The estimated effect of informal institutions is slightly larger for materials with 12.6% compared to 12% for CO_2. When generating a variable that combines formal and informal institutional quality in one variable (Model 3), the effect is again slightly stronger for CO_2. For both EI categories, the effect of the combined institutional variable is larger than for the formal institutional variable only.

To understand this relatedness of the two institutional variables in more detail, Figure 1 displays the relationship of the formal and informal institutional variable. It can be seen that there is a tendency of a positive coupling between both formal and informal institutions. Still, the two dimensions also introduce a certain degree of heterogeneity as can be seen by the fact that countries with similar formal institutions, such as Lithuania and Slovakia, differ strongly with respect to their informal institutions. Similarly, while Portugal and Germany score high in both institutional dimensions, Portugal has the strongest informal institutions, and Germany has the strongest formal institutions. Ireland is the most striking counterexample, as it has strong formal institutions, but underperforming informal institutions.

The effects of our control variables confirm our expectations, as all variables positively affect the probability that a firm will introduce an EI. The largest effect is found for Size, as the difference in probability between the smallest and largest firms is estimated as ~13%. Table 5 details our estimation results for the CIS 2014 wave.

Table 5: Results of probit models for the CIS 2014

	(1)	(2)	(3)	(4)	(5)	(6)
Analysis type	Univariate Probit	Univariate Probit	Univariate Probit	Univariate Probit	Univariate Probit	Univariate Probit
Dep. Var.	Ecomat	Ecoco	Ecomat	Ecoco	Ecomat	Ecoco
Inst. Var.	Model 1	Model 1	Model 2	Model 2	Model 3	Model 3
iForm	.1539***	.3196***	.0355***	.1858***		
iInf			.1745***	.2131***		
iForm*iInf					.1833***	.3409***
Size	.1848***	.2355***	.2048***	.2599***	.1923***	.2502***
Group	.0196***	.0197***	.0274***	.0294***	.0276***	.0363***
International	.0260***	.0172**	.0209***	.0126*	.0334***	.0303***
Sectors	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	23873	23873	23873	23873	23873	23873

Notes to Table 5: *Marginal effects at the means are reported. Concerning dummy variables the values report the change in probability for a discrete change of the dummy variable from 0 to 1.*
*For continous variables (Size, iForm, iInf, iForm*iInf) we report the change in probability when varying the concerned variable from the minimum to the maximum value.*
, **, * denote significances of the marginal effects at the 10%, 5%, and 1% level, respectively.*
Ind. Dummies (Sectors), at the most detailed level provided in the CIS data, are included but not reported. The constant is not reported. Robust standard errors were used.

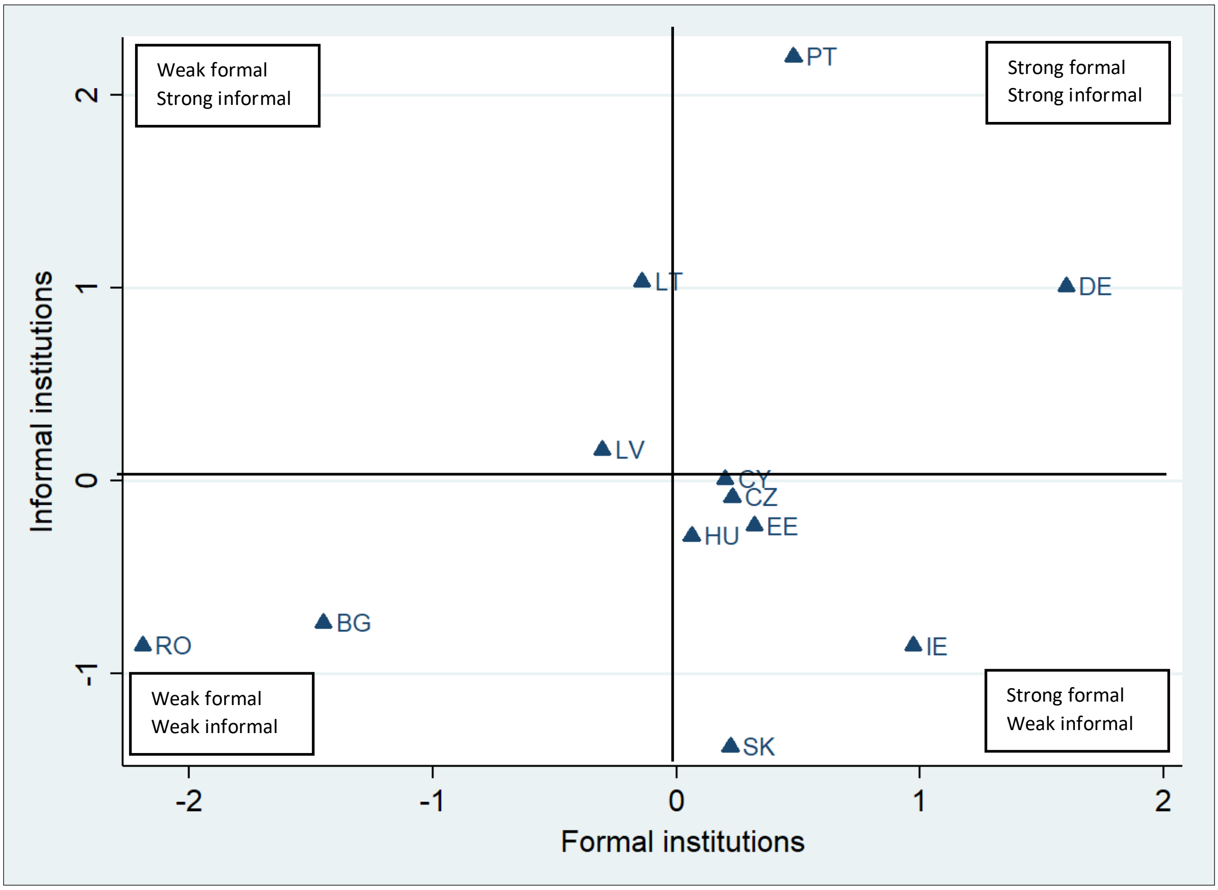

Figure 1: Formal and informal institutions for the CIS 2008

Comparing the effects between the two samples should be treated with caution, as we cannot identify the extent to which the firms surveyed in the two waves overlap. However, given the large number of firms surveyed in each country we consider it justifiable to compare the results.

The effect of formal institutions (Model 1) is again positive and highly significant. For Ecomat, the effect is a little larger than in the CIS 2008, with an estimated effect of 15.4%. For Ecoco, there is a substantial increase in the impact of formal institutions as the effect increases to 32%, more than twice as large as the CIS 2008 sample.

When including informal institutions in our CIS 2014 model (Model 2), the observation from the CIS 2008 is confirmed, as the effect of informal institutions are estimated to be larger for both EI categories. For Ecomat, the effect of formal institutions is even smaller, at 3.6%, while the effect of informal institutions is a little larger, 17.5%. For Ecoco, the opposite observation holds concerning the ratio of the two institutional dimensions. Formal institutions exert a substantially larger effect in the CIS 2014 sample than in the CIS 2008 sample, estimated at 18.6%. Although the effect of informal institutions also increases from 12% to 21.3%, the measure of the effect of the two institutional dimensions on Ecoco are now almost equal. Thus, it can be generally stated that the influence exerted by institutions has changed over time. Formal institutions are less relevant for Ecomat, whereas informal institutions appear to be more significant. On the other hand, both institutional dimensions exert a more significant impact on Ecoco. The effect of informal institutions almost doubles, and the effect of formal institutions almost triples. Hence, the opposite holds for Ecoco, as formal institutions are relatively more important for the CIS 2014. The interaction variable (Model 3) for both institutional dimensions supports this pattern, as the effect settles at 18.3% for Ecomat, and 34.1% for Ecoco.

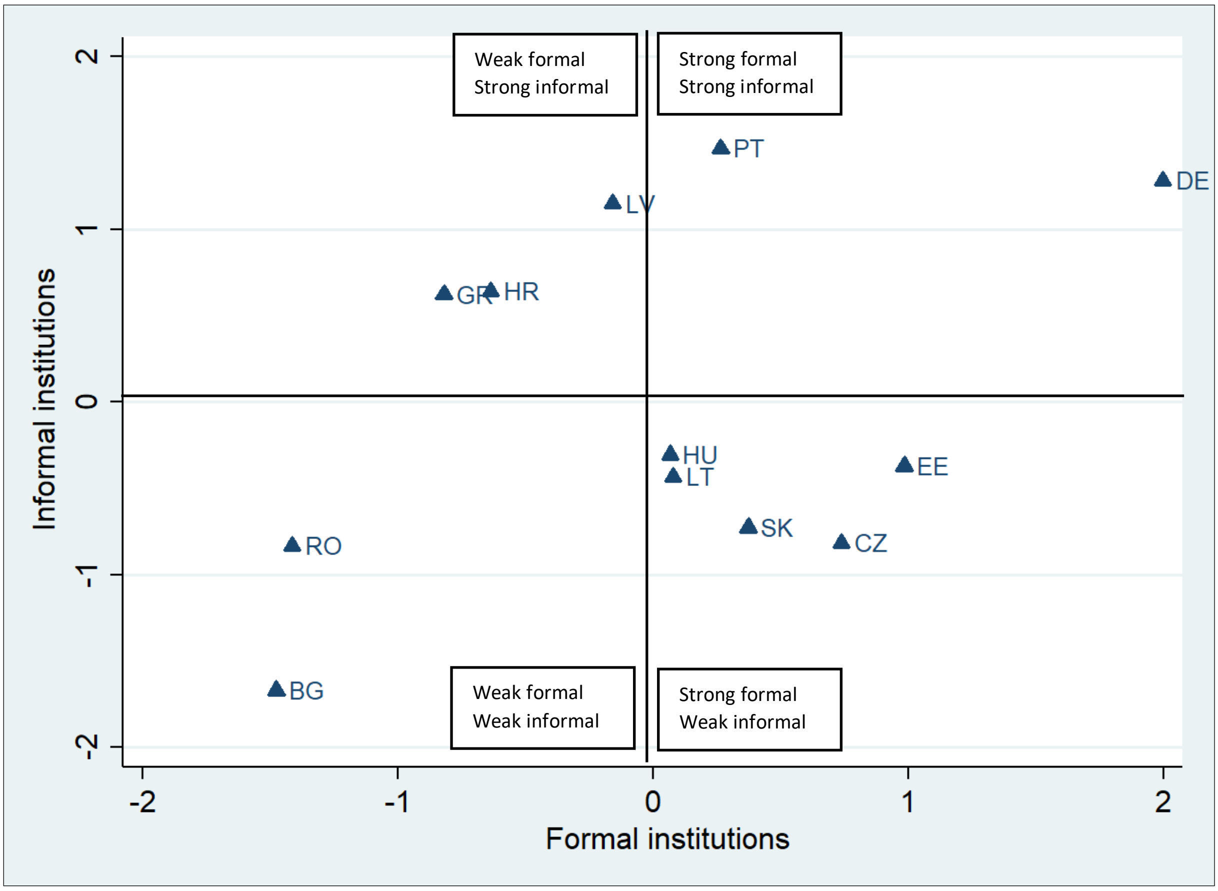

Figure 2: Formal and informal institutions for the CIS 2014

Figure 2 displays the relatedness of formal and informal institutions for the second CIS wave. Again, a positive coupling of the two dimensions seems evident. Yet again, each country shows unique patterns of the formal/informal relationship. Further, while the general structure of the country positioning remains quite similar, certain changes emerge. This includes the shift between Romania and Bulgaria, with Romania now outperforming Bulgaria, or the changes of position between Lithuania and Latvia, as the informal institutions of Latvia have substantially improved, while Lithuania reverted.

The results of our additional control variables confirm our expectations. All variables are again highly significant and positive. The only exception is our variable International in the case of Ecoco. The effect of Size is more pronounced, ranging at ~20% for Ecomat and ~25% for Ecoco.[33] The effect of Group is more homogenous than for the CIS 2008 as the effect is ~3% for both EI types. International again has a larger effect for Ecomat, although the differences to the effects for Ecoco are also substantially smaller.

2.5.2 Robustness Checks

To validate our findings, we ran several robustness checks. First, we ran our models using bivariate probit models, as the dependent variables may be correlated. Second, we included an additional control variable, namely whether a firm qualifies as a Foreign Direct Investment firm (FDI).[34] This may be relevant, as FDI firms can be affected by institutional pressures relevant in the group's head office country, while at the same time technology import may be affected. Third, we used an alternative way to investigate the role of institutions. Following Bryan and Jenkins (2013), we estimated our probit models with country-fixed effects instead of the institutional variables. Then, we regressed the country-fixed effect on our institutional variables using OLS. Fourth, for both survey waves we excluded the two countries that are included in only one wave, in order to determine the robustness of our results for the identical ten country sample. Last, we used general innovativeness as a dependent variable.

Similar to the findings of Horbach (2016) and Garrone et al. (2018), the results did not change in a meaningful way when using a bivariate probit, nor when including FDI as another firm-level control variable. Hence, we saw no need to refrain from using univariate probit, nor to include FDI into our general models. As stated in the methodological section, our analysis may

[33] Note that differences in Size effects may be due to differences in the size classes between CIS 2008 and CIS 2014.
[34] A firm is defined as an FDI firm if it belongs to a group with the head office located abroad.

suffer because of having so few countries in our samples. Hence, to check our findings, we use OLS to analyse the effect of our institutional variables on the country effects, which are obtained from the probit analysis of our entire sample (Bryan and Jenkins, 2013). The results are provided in Table 6.

Table 6: Results of OLS regressions for country-fixed effects

	(1)	(2)	(3)	(4)
Analysis type	OLS	OLS	OLS	OLS
Dep. Var.	Ecomat 08	Ecoco 08	Ecomat 14	Ecoco 14
Model 1				
iForm	.1271 (0.163)	.1861 (0.164)	.1115 (0.210)	.2220* (0.070)
Model 2				
iForm	.0949 (0.334)	.1472 (0.345)	.0312 (0.680)	.1262 (0.205)
iInf	.0838 (0.312)	.1009 (0.383)	.1970** (0.011)	.2347** (0.010)
Model 3				
iForm*iInf	.1675*** (0.009)	.2188** (0.012)	.1618*** (0.003)	.2623*** (0.000)
Obs.	12	12	12	12

***Notes to Table 6**: Robust standard errors were used. The constant is not reported.*
*The coefficient and the p-value (in brackets) are reported. * $p<0.1$; ** $p<0.05$; *** $p<0.01$*

Focusing on Model 1 with formal institutions only, our main insights are confirmed. The estimated effect of formal institutions is larger for Ecoco for both CIS waves. Also, the difference between Ecomat and Ecoco is more pronounced for the CIS 2014 wave, as the estimated coefficient becomes larger for Ecoco, while becoming slightly smaller for Ecomat. The coefficient for Ecoco for the CIS 2014 is significant at the 10% level.

Model 2 also confirms our main insights. The effect of formal institutions is stronger for Ecoco for both CIS waves, yet the difference with Ecomat is more pronounced for the second wave. This OLS regression reveals that the coefficient of formal institutions is smaller for the second wave in the case of Ecoco, which is a difference compared to the main results. The findings on informal institutions also support our main results. The impact of informal institutions is similar for both EI categories and waves, the gap between the effects of formal and informal institutions becomes substantially larger for Ecomat than for Ecoco. Further, the effect of informal institutions is substantially larger for the second CIS wave, reflected by the informal coefficient being significant at the 5% level for both EI categories.

Model 3 explores the relation of our interacted institutional variable with the country effects. Again, the main findings are confirmed. Specifically, the effect is stronger for Ecoco, and the gap between Ecomat and Ecoco is larger for the second CIS wave. Note that the coefficient for Ecoco increases by roughly one fourth, whereas it decreases slightly for Ecomat. For all four specifications, the interaction variable is significant at the 5% and 1% level, respectively.

To understand these results in more detail, we plot the country effects against our interacted institutional variable, following Bryan and Jenkins (2013). We create separate graphs for each EI category for the second CIS wave (CIS 2014). Figure 3 plots the country-fixed effects from the analysis for Ecomat.

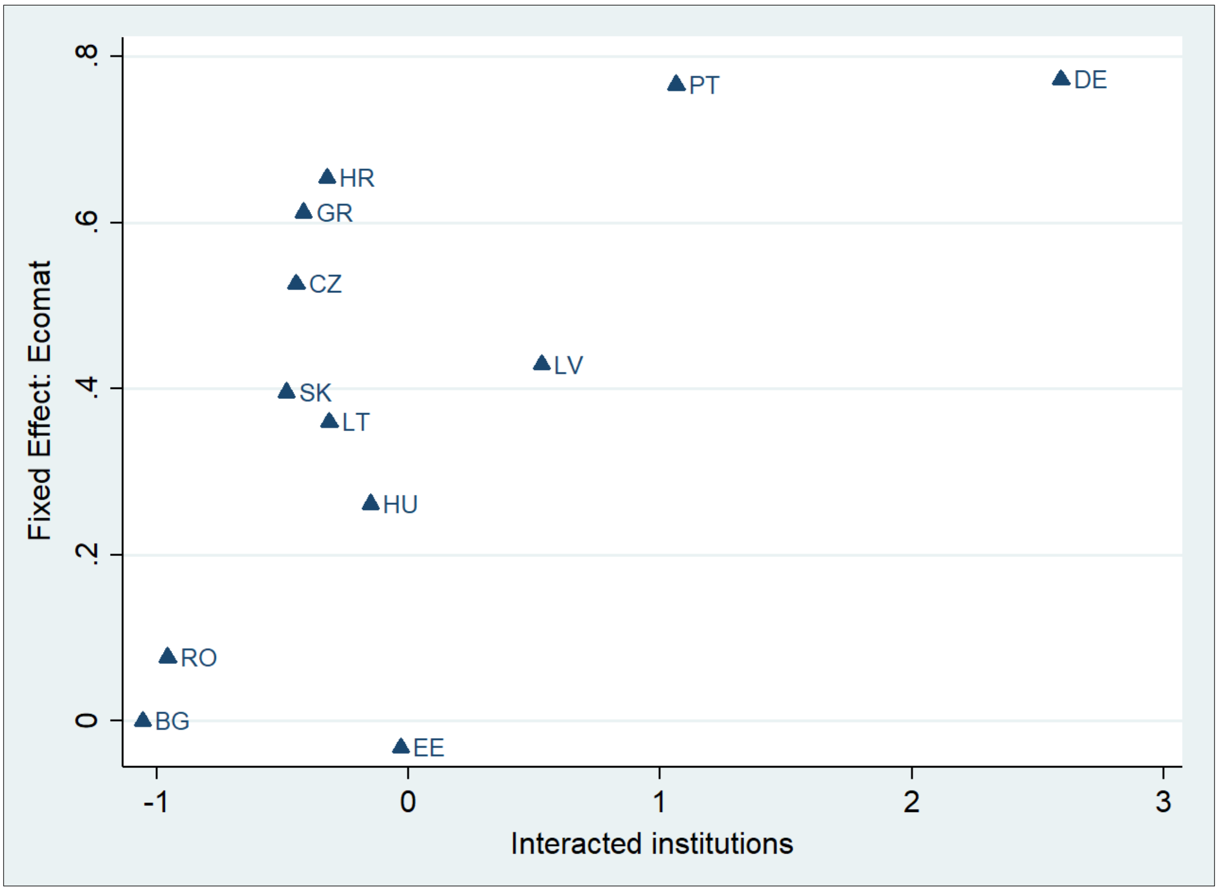

Figure 3: Country effects and interacted institutions for Ecomat

The graphic presentation of our regression results (Table 6, Model 3, Column 3) seen in Figure 3 provides some interesting insights. The country effect ranges from slightly below 0 to 0.8. Further, most countries are close to 0 for the interacted institutional variable. Yet, the country effect for these countries ranges from below 0 to over 0.6. It appears that this heterogeneity of country effects cannot be attributed to the institutional variable. Thus, the clear statistical relationship seems to be driven by the countries underperforming institutionally (Romania and Bulgaria), and those overperforming (Latvia, Portugal, and Germany). The country effect of Bulgaria and Romania is second and third lowest, ranging around zero. The country effect of Latvia at 0.4 is moderate, but Portugal and Germany have the highest country effects of more than 0.75, corresponding to the highest institutional values of 1 and almost 3, respectively.

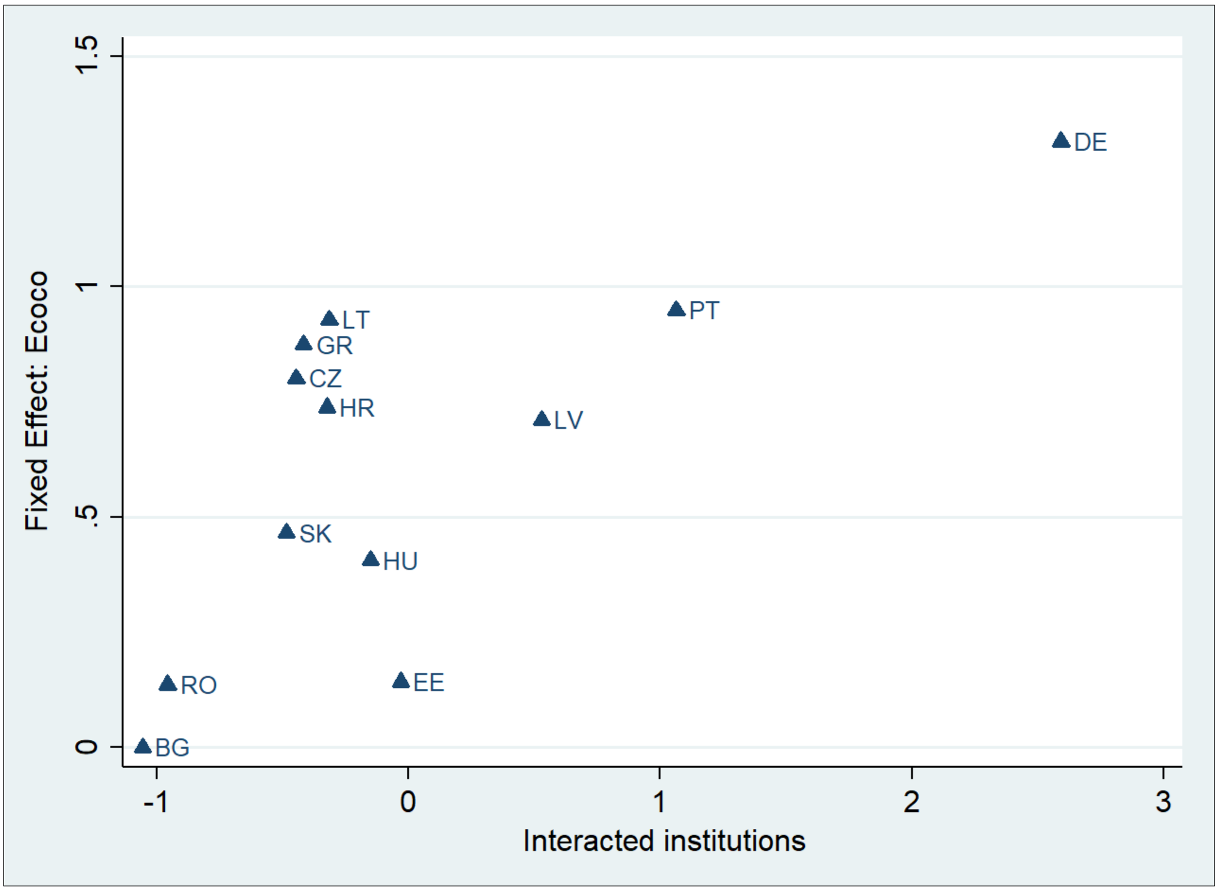

Figure 4: Country effects and interacted institutions for Ecoco

Figure 4 plots the country effects obtained from the analysis of Ecoco (Table 6, Model 3, Column 4). Interestingly, the emerging structure is very similar to the structure for Ecomat. The main difference seems to be the size of the country effect that ranges from 0 to 1.3. Given the similar structure of the two graphs, it seems plausible that the higher coefficient is mostly driven by the different range of the country effect for Ecoco. These graphical investigations seem to show that our institutional variable is a good indicator of the relative quality of the institutional environment of the countries included in our analysis. Yet, the clear heterogeneity of the country effects coefficient for those countries ranging around 0 for the institutional variable, cannot be sufficiently related to our institutional measure.

When focusing on only the ten countries present in both survey waves (excluding Ireland and Cyprus from the first, and Croatia and Greece from the second wave), there are several observable differences. For the CIS 2008 wave, the results for Ecomat remain basically the same. For Ecoco, however, the effect of formal institutions is reduced to 4% and the effect of informal institutions increases to 15.7%. In other words, if we focus on the two areas of environmental concern, the effect of informal institutions is stronger for Ecoco in the ten country analysis (full sample: stronger for Ecomat), and the effect of formal institutions is slightly stronger for Ecomat in the ten country analysis (full sample: stronger for Ecoco). For CIS 2014, the differences are similar for both EI types. The effect of formal institutions is more pronounced and the effect of informal institutions is less pronounced in the ten country sample. In the case of Ecoco, the effect of formal institutions is estimated to be ~4% higher than the effect of informal institutions in the ten country sample (full sample: the effect of informal institutions is ~3% larger).

As a final robustness check, we used a dichotomous innovation variable to capture whether or not a firm introduced any type of innovation. We conduct this investigation to ensure that our measures of institutions are specifically relevant in the context of EI. The results confirmed that our formal institutional measure is more positively related to increasing the introduction of the analysed EI types than general innovation. This robustness check follows Garrone et al. (2018) and is a way to show that the institutions are not generic indications of a country's progress. The results will be discussed in more detail in the next section.

2.6 Discussion and Conclusion

In this study we investigate the role of both regulatory (formal) and social (informal) institutional pressures on the development of environmental innovation designed to address two substantially different types of environmental issues, namely: reducing material use and/or reducing CO_2 emissions. By utilizing the CIS 2008 and 2014 waves, we are able to investigate the institutional effects at two different points in time separated by a six-year gap. We find that formal institutions are more strongly related to the introduction of EI aimed at reducing CO_2 emissions. Regarding effect size, informal institutions are found to be the institutional dimension with the more significant impact.

Our general finding that stronger institutional pressures are associated with the introduction of EI are in line with similar studies (Berrone et al., 2013; Liao, 2018). Analysis on the reasons for EI introduction based solely on the CIS data finds similar relationships (Horbach, 2016). Namely, regulation and subsidies – qualifying as formal institutions – are substantially more closely associated with emission innovation than with EI related to material use (Horbach, 2016). While demand is found to be similarly related to the two EI types, cost savings are substantially more important for material use innovation (Horbach, 2016). Garrone et al. (2018) find partially different results concerning energy efficiency innovations in European countries. They find that formal institutional pressures affect both product and process energy efficiency innovations, while informal institutional pressures only affect product innovations (Garrone et al., 2018). Our results indicate that informal institutions also affect process innovations, a finding that draws into question the generalisability of the conclusions drawn by Garrone et al. (2018). However, while reduction of material use is reflected by the market to some degree via prices, CO_2 emissions may be a more prominent issue for public pressure than reducing energy inputs. Further, normative pressures may demand and facilitate more fundamental responses than formal measures (Berrone et al., 2013). In this vein, the increasing importance of formal institutions for emissions may be related to more stringent and effective regulations, making it more difficult to simply comply via symbolic efforts (Berrone et al. 2013).

When comparing the results for the two CIS waves we find that, overall, formal institutions have more of an impact on the introduction of EI aimed at reducing CO_2 emissions. The CIS 2014 wave reveals that the gap between the effects of formal institutions on emission reduction and material use reduction is substantially larger. We interpret this result as an indication that, in relative terms, formal institutions become more important specifically for emissions reduction, over time. When comparing the interrelation of the two institutional dimensions, we find mixed evidence for emission reduction innovation,[35] while in the case of material use innovation informal institutions are gaining in relative importance. Generally speaking, the estimated effect of institutions is more pronounced for the second sample (CIS 2014).

Our curiosity about EI is driven by the fact that differences between countries concerning the introduction of EI persist, and these differences cannot be explained exclusively by firm-level determinants. We attempt to explain these difference by accounting for the role of both formal and informal institutional pressures that may influence firms' strategies. However, as shown in Figures 3 and 4, substantial dynamics in country effects cannot be directly related to the measured institutional differences.[36] From a theoretical perspective, institutional pressures are expected to positively affect the introduction of environmental innovation. Empirically, the influence of these pressures are found both by pertinent previous studies, and can be contended from our analysis as well. Nevertheless, as we are constrained to cross-sectional data, statements about directions of causality or the addressing of endogeneity issues is difficult (Mairesse and Mohnen, 2010). Especially, we cannot control unobserved heterogeneity due to the lack of this temporal dimension (Mairesse and Mohnen, 2010). Institutional measures may

[35] The results of OLS (Table 6) and the main analysis differ (Tables 4 and 5). In the main analysis, formal institutions gain in relative importance compared to the effects of informal institutions, whereas in the OLS analysis informal institutions gain in relative importance. These differences could be due to the different model types employed.

[36] Note that this concerns the interacted institutional measure. Although the structure is similar for the formal or informal institutional variable.

be correlated with other country characteristics, such as technological capabilities. Further, the level of analysis may play a role as well. Firms are not only embedded in the national context, but likely also dependent upon more specific regional contexts (Berrone et al., 2013). More specifically, firms are affected by very specific regulatory and normative pressures that can vary at very detailed sectoral and regional levels and cannot be captured in our empirical setting. Moreover, firm-specific characteristics, such as the relative environmental performance of a company, has been shown to play a role (Berrone et al., 2013), yet cannot be sufficiently controlled with the utilized datasets.

Our work provides evidence that the introduction of different EI types is, to a varying degree, related to the presence of institutional pressures in the concerned country. The evidence presented should be treated with caution, due to the data employed in our study. We emphasize, however, that the distinction of EI types and the corresponding relevance of different institutional pressures is a research program worthy of further investigation. Progress on this subject will require more detailed analysis of institutional pressures, especially at higher levels of disaggregation with respect to sectoral and regional environments. The availability of data sources that allow for a panel data structure to control unobserved heterogeneity in firm's initial conditions will be an important prerequisite.

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Chapter 3

The Impact of Environmental Innovation on Carbon Dioxide Emissions

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Abstract

This paper examines the effects of environmental innovation on carbon dioxide emissions in the EU-27 countries between 1992 and 2014. We utilize the Generalized Method of Moments in a dynamic panel setting. Patent counts of environmental patent applications are used as indicator for environmental innovation. We find that environmental innovation did contribute to reductions of carbon dioxide emissions, while general innovative activity does not cause decreases in emissions. However, this effect is found to be comparatively small to the effects of increased economic activity. Further, we find the effect of innovation to differ across countries, with less developed economies showing a higher level of heterogeneity.

Keywords: Dynamic panel ® Carbon dioxide emissions ® Environmental innovation ® Patent data ® Sustainable development ® Green technological change

JEL Classification: O33; O44; Q01; Q54; Q55

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3.1 Introduction

Since approximately 1750 the atmospheric greenhouse gas (GHG) concentration and the global mean temperature have been dramatically increasing (Boeker and Van Grondelle, 2011). About that time the industrial revolution started. There is general consensus that those processes are interlinked. To allow for industrialization and general development humans have harnessed non-anthropogenic sources of energy (Cordes, 2009), mainly fossil fuels and biomass which release GHG during combustion (Boeker and Van Grondelle, 2011). The natural greenhouse effect that is essential for the formation and preservation of life on planet Earth (Boyes and Stanisstreet, 1993), has been significantly intensified since human activity showed an impact on environment, leading to climate changes and globally rising temperatures. As carbon dioxide (CO_2) is emitted in high quantities and has a high concentration in the atmosphere, it is internationally of most interest. This global warming will potentially have a multidimensional impact on the Earth's ecosystem and humanity, like e.g. intensifying dry-seasons, causing great challenges regarding food and drinking water supply, raising sea levels, causing changes in the Earth´s geography, increasing the fire frequency, increasing desertification (Solomon et al., 2009), and increased frequency and intensity of storm disasters (Reuveny, 2007). These developments combined are expected to increase migration, entailing the potential for violent-conflicts, and friction between globally leading powers (Reuveny, 2007), potentially leading to future wars (Hopwood et al., 2005).

The urgency to handle these problems has led to a higher priority on political agendas. The idea of unlimited economic growth has been increasingly questioned. Influential reports, especially *The Limits to Growth* (Meadows et al., 1972) have helped to bring environmental problems into political debates. In the following years the generic term *Sustainable Development* was adopted to describe a general development towards a system and system structures combining a range of environmental and socio-economic issues (Hopwood et al., 2005). A central approach to facilitate this development is a techno-centered one. Therein, technology plays a key role in encountering future problems, by either substituting natural resources (Solow, 1974) or helping to protect the environment (Hopwood et al., 2005). In general, this focuses on the idea of shifting the current and rather fossil fuel-based technologies towards more ecologically friendly ones. It is claimed that those new technologies will provide wider economic, social and environmental benefits (Hopwood et al., 2005), and thereby somehow help to overcome those "limits to growth".

The European Union (EU) has set different climate political minimum targets to encounter current and future environmental developments, like a 40% reduction in CO_2, an increase in the share of renewable energy of 32%, and an increase in energy efficiency of 32.5%, compared to the levels of 1990 (European Commission, 2019). The long-term aim is to make the EU a resource-efficient, green and low-carbon economy that is internationally competitive (European Commission, 2011). One central instrument in that mission is the strategic promotion of green technologies and ecologically relevant innovations, implemented by the Eco-Innovation Action Plan. By systematically fostering environmental innovations,[37] a new technological level based on those green technologies is to be created in the long term. Those technologies are expected to be more carbon and resource efficient and thus allow for sustained economic activity and wealth, decoupled from ecological deteriorations. Thus, a political strategy, aimed at fostering such a *green technological change*, seems to be a proper approach to encounter environmental problems. To quantify and evaluate the actual effect of those green technologies is the aim of this study.

Although there is a substantial amount of literature dealing with means to foster those green technologies and their potential effects, studies investigating the concrete effect are only scarce (Barbieri et al., 2016). The present study aims at identifying the effect of environmental innovation (EI) on carbon dioxide emissions. Since EI is hypothesized as a solution approach, it is essential to analyze and evaluate its effect, and thus its ability to encounter global warming and related problems. This analysis is based on the EU-27 countries. These countries are chosen because they are both economically and politically strongly connected, given the shared EU framework (European Commission, 2011, 2010) and due to the above mentioned program. This study especially contributes to this literature twofold. First, to the best of our knowledge, it provides the first cross-country analysis on the national level on the impact of EI. Second, all analysis is based on the absolute levels of measures, not relative ones that could be considered a drawback of many earlier studies to a certain degree. Within the Kyoto Protocol framework, environmental measures are evaluated by the percentage reduction of the total CO_2 level (Friedl and Getzner, 2003). Furthermore, relative measures can decrease, while the absolute level is still increasing. Therefore, this study aims at the absolute impact of EI and its potential to tackle environmental problems and climate change. Hence, both aspects are contributing to the

[37] In the following, the terms environmental innovation and environmental innovative activity will be used interchangeably. The latter term refers primarily to our empirical operationalization of the innovation process.

literature and quality of insight into the effects and relevancy of EI, as a realistic and reliable means to base future economic and policy decisions on.

The paper is structured as follows. Section two will review the relevant background literature and theoretical ideas regarding environmental innovation. Furthermore, an overview of the relevant empirical studies will be given. Section three presents the dataset and section four the methodology. The estimation results and robustness checks will be given in section five and will be discussed and concluded in section six.

3.2 Literature Review

This paper draws upon the literature on the environmental effects of EI, as well as on the literature concerning determinants of CO_2 emissions. First, we will provide considerations on how environmentally innovative activity is interrelated with environmental regulation and the adoption of green technologies. Second, we will review previous papers on the environmental effects of EI. Lastly, we will review the literature on the determinants of CO_2 emissions to consolidate our empirical decisions.

Incremental and radical improvements in technologies are a key component of the international agenda to encounter environmental problems and climate change. The concept of *technological change* is widely discussed in the literature (Acemoglu, 2002; Acemoglu et al., 2012; Jaffe et al., 2002; Popp et al., 2011, 2010) as a means to achieve the long-term goal of sustainable economic growth (Popp et al., 2010), since the existing and upcoming environmental problems are not adequately addressable with the current technological level (Popp et al., 2010).

Environmentally innovative activity (EI) only relates to improvements in environmental performance when technologies are diffused and applied (Popp et al., 2010; Sarr and Noailly, 2017). EI can affect environmental performance through different channels (Barbieri et al., 2016), for example via spillovers to other regions and sectors (Cainelli and Mazzanti, 2013; Corradini et al., 2014; Costantini et al., 2013; Dechezlepretre et al., 2014). Although EI is not equivalent to adoption, these processes are highly interlinked. Incentives, such as regulation, affect any stage of the innovation process, including development and diffusion (Popp, 2005). Regulation and external pressure have been shown to foster the adoption of environmental technologies (Blackman and Bannister, 1998; Kemp, 1998; Kerr and Newell, 2003; Popp, 2010; Popp et al., 2007; Snyder et al., 2003), with the adoption potentially being quickly conducted in response (Lovely and Popp, 2007). While the most recent environmental technologies may rather be applied in response to regulatory pressure, technological advances can support the adoption of existent environmentally favorable technologies (Popp, 2006). However, even in presence of weak policy stimulus EI may be spurred by firms (Ghisetti and Quatraro, 2013). In order to adopt a technology, domestic innovation is often needed to match the local market (Popp, 2006). At the firm level such technological activities improve absorptive capacities, facilitating the diffusion of external technology (Fisher-Vanden et al., 2006).

Environmentally innovative activity[38] is at the core of the interrelation between regulation and adoption. The anticipation of higher regulation is likely reflected in a heightened innovative activity (Carrión-Flores and Innes, 2010). Innovative activity in turn induces a further tightening of standards (Carrión-Flores and Innes, 2010) and is likely associated with the adoption of already existent[39] environmental technologies by firms (Popp, 2010). Further increases in regulatory stringency facilitate the adoption of the latest and most advanced technologies (Popp, 2010),[40] which then can allow a further tightening of standards. In the same vein the initial increase in regulatory standards likely results in the expectation of increasing standards, which then again heighten innovative activity.

Hence, we consider EI as indicative for internal and/or external pressure to develop and adopt new technologies, alongside the technological capabilities (Costantini et al., 2017) to create and adapt environmentally favorable technologies.

Environmental innovation can easily be linked to environmental relievements and emissions reduction. Innovations within the area of renewable energy production like solar or wind energy reduce energy consumption related emissions. New types of bio-fuels or more efficient vehicles may reduce mobility related emissions. Those simple examples intuitively suggest a positive effect of EI.[41] Clarity concerning the concrete impact of EI is not yet given and empirical studies investigating this effect are still scarce. Nevertheless, an increasing number of recent studies enable insights into potential effects. Concerning environmental productivity, EI is suggested to contribute to less emissions per unit of output. This is supported by Weina et al. (2016), finding a significant impact of EI on environmental productivity, hence reducing emissions per

[38] Measured by environmental patent applications.
[39] Already existent environmental technologies refer to technologies which have already been adopted by some actors, and are now adopted by latecomers. The environmental performance of these latecomers is improved by applying these technologies.
[40] Latest and most advanced technologies refer to technologies which are just developed and now raise the technological possibilities.
[41] Positive here refers to the fact that reducing emissions by EI is the desired outcome. However, in the course of this study we will now speak of a reducing or negative impact as from the statistical point of view this effect is shown by a negative coefficient of our EI variable.

unit of output, as well as Costantini et al. (2017) finding a significantly negative effect on sectoral environmental intensity. Ghisetti and Quatraro (2017) support these results, finding a positive impact on the environmental productivity of regions sectors. A study feeding into these results is Wurlod and Noailly (2016) finding a negative impact of EI on the energy intensity of industrial sectors in OECD countries. Assuming constant emission intensity of energy use, EI is thus suggested to have a negative impact on emissions. The effect of EI on the absolute level of CO_2 emissions is more inconclusive. Carrión-Flores and Innes (2010) find that first, tightened pollution targets have an impact on the cost-saving benefit of innovation activity, and second, environmental innovations do have a significantly negative impact on pollution emissions for US manufacturing industries. Wang et al. (2012) find that fossil fuel-related innovations do not have a significant effect on the reduction of emissions, while the effect of carbon-free energy innovations is unclear. Only at the regional level a significantly negative effect is partially found, while on the national level no significance is evident. Weina et al. (2016) do not find a significant effect on the total level of CO_2 at all, while Zhang et al. (2017) find a reducing effect on CO_2 per capita in Chinese provinces.

There is a vast amount of literature dealing with the determinants of CO_2 emissions. Economic growth is said to be one of the main drivers of CO_2 (Friedl and Getzner, 2003; Hossain, 2011; Sharma, 2011). When an economy grows,[42] the rate of flow of matter and energy through the economy increases, more resources are extracted from nature and more waste is released to it (Daly, 1987) – in this case in the form of CO_2. Economic growth is closely interconnected to energy usage, why its production and consumption are regularly described as a further major determinant (Hossain, 2011; Iwata et al., 2012; Sharma, 2011). The more energy is consumed, the more fossil fuels are needed to generate that amount of energy and consequently more CO_2 is emitted to the atmosphere. While economic growth captures a variety of structural changes and effects, energy consumption represents a more direct determinant of CO_2. Both measures represent the physical scale of the economy. Since earlier studies tend to suffer from an omitted variable bias, recent studies include a variety of further hypothesized climate relevant determinants (Kasman and Duman, 2015). Based on the importance of changes in the energy structure of an economy towards less carbon intensive sources, renewable energy technologies are seen as an important aspect of environmental sustainability (Dincer, 2000; Dogan and Seker, 2016; Panwar et al., 2011). The industry sector is assumed to be more emission intensive than the service sector, due to more energy and resource intensive processes (Carattini et al., 2015).

[42] Ceteris paribus.

The economic structure and the share of industry are thus hypothesized to determine the economy´s emissions (York et al., 2003). Trade is also said to have an influence (Ertugrul et al., 2016). The trade volume increased dramatically during the last decades and a vast amount of goods and services, even whole industries were shifted over time (Ertugrul et al., 2016). The concrete expected effect of trade on the environment is somehow inconclusive, since trade does capture different opposed effects. The most substantial is the so-called *carbon-leakage*, meaning that emission intensive industries and productions are shifted from developed economies - to improve their environmental conditions - to developing ones deteriorating environmental conditions there, such that the global emissions remain unchanged. A further potential force is the globally occurring change in the population structure from rural living environments to urban ones (He et al., 2017; Martínez-Zarzoso and Maruotti, 2011; Sadorsky, 2014). The concrete effect of this development on emissions is inconclusive. Urbanized areas are more population dense requiring more energy than rural areas and are facilitating economies of scale in production in the form of industrial concentration that requires additional transportation (He et al., 2017; Martínez-Zarzoso and Maruotti, 2011). However, the increased agglomeration and centralization facilitate a more centralized and monitored carbon emission control and enforcement of environmental regulation as well as low carbon mobility, based on a centralized and environmentally friendly energy production.

3.3 Dataset

We construct a panel dataset on the EU-27 countries,[43] spanning a period from 1992 to 2014. We restrict our dataset to this time due to data availability of our dependent variable, i.e. CO_2 emissions. Given the upheavals in the wake of the Soviet Union`s breakdown, we can retrieve a balanced sample of our dependent variable from 1992 onwards, thus avoiding issues stemming from the redefinition of countries, e.g. Germany or Czechoslovakia. 2014 is the last year for which we could gather CO_2 data.

The CO_2 data is provided by the Carbon Dioxide Information Analysis Centre (CDIAC) located in Tennessee, USA. It is one of the most reliable, comprehensive and current databases for CO_2 data , containing emission data from 1751-2014 for every country in the world at a global, national and regional basis (Boden et al., 2017; Doda, 2014). Captured sources of CO_2 emissions are the burning of fossil fuels and the manufacture of cement. The data derived

[43] Croatia is not included in our dataset, as it joined the EU in 2013.

capture CO_2 based on the "territory principle", as used in the context of the Kyoto Protocol (Usubiaga and Acosta-Fernández, 2015). An alternative way would be to account by the "residence principle". Given our focus on the effects of innovation within a country we consider the "territory principle" superior for our analysis.

Our main explanatory variable is Environmental Innovation (EI). We capture EI by relying on patent applications as a proxy. Patents are considered to be the most appropriate proxy for innovation (Haščič and Migotto, 2015), as they measure intermediate output, they are quantitative and widely available, and provide a wealth of information due to disaggregation into technological classes. While some drawbacks of patent data are extensively discussed in the literature (Haščič and Migotto, 2015; Johnstone et al., 2010; Lanjouw and Mody, 1996; Popp et al., 2011), patent data is considered as a preferable indicator for innovation (Dernis and Khan, 2004; Griliches, 1990).

To meet the issue of differing propensity to patent, as well as large value differences in patents we rely on patent applications at the European Patent Office (EPO) meaning multinational patent applications. Multinational patents are considered to indicate inventions of higher value as only the expected commercial profits justify the relatively high application costs (Johnstone et al., 2010). We include only the first patent of a patent family to avoid double counts of the same technology. Further, relying on one patent authority mitigates the issues stemming from differing patent regimes.[44] We assign the country based on the applicant data (Ghisetti and Quatraro, 2017) as we are interested in the utilization of an invention. We count the number of patents per country and year, where at least one of the applicants comes from the country concerned. We use patent applications instead of granted patents and include them based on their earliest filing year, to timely capture the whole innovative effort that has been undertaken (Costantini et al., 2017). Using patent applications is common (Costantini et al., 2017; Ghisetti and Quatraro, 2017; Wang et al., 2012; Weina et al., 2016) to capture the whole innovative effort independent of the sole economic market value (Costantini et al., 2017). The earliest filing year is the closest to the actual date of invention (Carrión-Flores and Innes, 2010; Costantini et al., 2017), not dependent on administrative procedures as the publication year is.

To distinguish environmental and non-environmental innovation we rely on the technological classes of patent applications, namely the International Patent Classification (IPC) and the Cooperative Patent Classification (CPC). Those have been made available to allow the

[44] It should be noted that given our model (First Difference model) differences in countries propensity to patent should not bother too much, as the change in patenting activity within one country is of interest, not the relation between different countries.

discrimination between green and non-green technologies (Ghisetti and Quatraro, 2017). Our search strategy used to construct our main explanatory variable is combining the technological classes from the OECD EnvTech and the WIPO Green Inventory (Haščič and Migotto, 2015; WIPO, 2012) that are widely applied in the literature to capture green technologies (Albino et al., 2014; Costantini et al., 2017; Ghisetti and Quatraro, 2017; Kruse and Wetzel, 2014).

We include a variety of variables to control potential aspects that affect carbon dioxide emissions, different than green innovation. We include GDP and energy consumption as proxies for the scale of the economy. Data on GDP is retrieved from Cambridge Econometrics European Regional Database (ERD).[45] Data on energy consumption is retrieved from Eurostat (see Carattini et al., 2015). Beside these explanatory variables we control for several further factors. Structural changes in the composition of an economy are considered to potentially influence emissions (Carattini et al., 2015), hence we calculate - based on the gross value added data from the European Regional database (ERD) - the share of the industry sector in the value added of an economy. Next to the economic structure, especially the energy supply structure may have an effect on the environmental impact of an economy (Weisz et al., 2006). Due to this we control for the share of renewable energy in the energy consumption of a country, also retrieved from Eurostat. Technological improvements may not only result from domestic innovation, but can also stem from the import of foreign technologies. Hence, we control for the net inflows of foreign direct investment (FDI) as a share of GDP. In a similar vein, trade openness[46] is considered to capture the potential of outsourcing of environmentally intensive production, leading to so-called carbon leakage (Carattini et al., 2015). Lastly, the population structure may indicate differences as the urban population may be more prone to lead a certain fossil fuel based industrial lifestyle (Shao et al., 2017). Therefore, we use the share of the urban population as a proxy. The data for our variables on FDI, trade openness and urban population is retrieved from the World Bank. A list on data source, units and descriptive statistics on all our variables can be found in Table A1 in the Appendix. Stationarity of the variables was tested using unit root tests. Relying on the Fisher-test with drift, all variables are stationary except for the share of renewable energy (see Table A2 in the Appendix). A more detailed discussion of emission and patent data is provided in the Appendix (A3).

[45] The data is publicly available at https://urban.jrc.ec.europa.eu/t-pedia/#/

[46] Trade Openness is calculated as the sum of Imports and Exports as share of GDP.

3.4 Methodology

A dynamic panel data approach is employed in this study, since it is assumed that CO_2 is depending on itself from the last period. This is due to assumed gradual changes in the production structure of an economy (Ibrahim and Law, 2014).

$$(1)\quad CO_{2,i,t} = \sum_{j=1}^{J} \delta_j CO_{2,i,t-j} + X'_{i,t}\beta + \mu_i + \psi_t + \varepsilon_{i,t}$$

$$with\ i = 1, \dots, N\ and\ t = 1, \dots, T$$

$CO_{2,t-1}$ represents the lagged dependent variable (LDV), X' is a $1\ x\ k$ vector of regressors, β denotes the $k\ x\ 1$ vector of coefficients, μ the country fixed effects, ψ the time fixed effects and ε the error term. The subscript i denotes the cross-sectional unit (country) and t denotes the time.

Employing the well-known Fixed-Effects estimator (FE), aiming to eliminate the country fixed effects, leads to endogeneity problems caused by the presence of the LDV (Baltagi, 2008). The FE estimator fails to eliminate all sources of endogeneity, known as the Nickell-Bias, which leads to inconsistent estimates (Nickell, 1981). Although this bias decreases with T increasing, it was shown that even with $T = 30$ the bias can be around 20% of the true coefficient value (Judson and Owen, 1999). A way to avoid this bias and general endogeneity problems is to utilize instrumental variable (IV) estimation methods.

Due to the given data structure this study employs the one-step difference Generalized Method of Moments (GMM) estimator, as proposed by Arellano and Bond (1991), widely known as the Arellano-Bond estimator (AB). This is in line with econometric literature suggesting the usage of this estimator, since it outperforms other methods in long panels (Hwang and Sun, 2018; Judson and Owen, 1999).

Starting point of the AB estimator is given by first-differencing the equation:

$$(2)\quad \Delta CO_{2,i,t} = \sum_{j=1}^{J} \delta_j \Delta CO_{2,i,t-j} + \Delta X'_{i,t}\beta + \Delta\psi_t + \Delta\varepsilon_{i,t}$$

This eliminates μ_i but causes that the LDV again is correlated with the error, due to $\Delta y_{i,t-1} = y_{i,t-1} - y_{i,t-2}$ and the existence of $\varepsilon_{i,t-1}$ in $\Delta\varepsilon_{i,t} = \varepsilon_{i,t} - \varepsilon_{i,t-1}$ (Baltagi, 2008). This problem is encountered by the utilization of IV, in which the first-differenced variables are instrumented by their own lags. Those are highly correlated with the LDV, but not correlated with the error. These estimators allow the inclusion of endogenous, predetermined and exogenous regressors. Endogenous regressors are influenced by the contemporaneous error term, while predetermined regressors may be influenced by the error term in previous periods. In this manner, the strictly exogenous variables are instrumented by themselves and the endogenous or predetermined by their lagged levels (Castro, 2013). Basis and suggested advantage of the GMM procedure is the comprehension of the orthogonality conditions, existing between y_{it} and ε_{it} that are the imposed moment conditions.

$$(3)\quad E\left[CO2_{i,t-s}\Delta\varepsilon_{i,t}\right] = 0 \quad and \quad E\left[X_{i,t-s}\Delta\varepsilon_{i,t}\right] = 0$$

$$for\; t = j+2, \dots, T \quad and \quad s \geq j+1$$

The procedure requires that no second-order autocorrelation in the differenced equation is present, while first-order autocorrelation is uninformative. Autocorrelation of order higher than one in the differenced equation would render some instruments invalid,[47] requiring later lags to be used as instruments causing a loss of observations (Roodman, 2009). If second-order autocorrelation would be present, this would generate inconsistent estimates (Castro, 2013).

Further, for the the validity of GMM exogeneity of the instruments is needed. If the number of regressors k is equivalent to the number of instruments j, then the model would be exactly identified, making detection of invalid instruments impossible. However, if the model is overidentified due to $j > k$, the validity of instruments is tested with the Sargan specification test (Castro, 2013; Roodman, 2009).

[47] Even after estimation with forward orthogonal deviations the test is run on residuals in differences (Roodman, 2009).

3.5 Empirical Results

We start by proving the soundness of AB estimation for our model and with the determination of the lag structure on our innovation variable. Further, we test a variety of determinants that have been considered in the literature for inclusion and determine our main model for further analysis. We then turn to test the robustness of our results by analyzing different samples of our dataset, testing an alternative green innovation search strategy, and exploring whether EI actually has a unique effect on carbon dioxide emissions or whether regular innovations provide a similar effect. Finally, we provide evidence that the effects of EI may differ across countries.

3.5.1 Main Results

We start by specifying a baseline model for our analysis (see Table 1), including the LDV, our main explanatory variable environmental innovation (EI), and the relevant scale variables, namely GDP and Gross Inland Energy Consumption (Energy) (Carattini et al., 2015).

Table 1: Baseline model with OLS, FE and AB and different lags of EI

	(1)	(2)	(3)	(4)	(5)
Model	OLS	FE DK	AB	AB	AB
Dep. Var.	CO_2	CO_2	CO_2	CO_2	CO_2
L1. CO_2	0.958***	0.338***	0.579***	0.540***	0.581***
	(0.0101)	(0.0568)	(0.143)	(0.170)	(0.161)
Environmental Innovation				0.00168	
				(0.00578)	
L1. Environmental Innovation	-0.00569**	-0.0120***	-0.0137**	-0.0132*	-0.0131**
	(0.00279)	(0.00423)	(0.00572)	(0.00661)	(0.00631)
L2. Environmental Innovation				-0.00360	-0.00340
				(0.00464)	(0.00474)
Energy	0.0289***	0.748***	0.501***	0.543**	0.486**
	(0.0107)	(0.0660)	(0.178)	(0.219)	(0.202)
GDP	0.0145*	0.125***	0.141**	0.131	0.146*
	(0.00827)	(0.0341)	(0.0680)	(0.0905)	(0.0787)
Time-effects	Yes	Yes	Yes	Yes	Yes
Observations	577	577	550	526	533
No. of Countries	27	27	27	27	27
R-squared	0.999	0.8806			
AR1-Test			-2.79	-2.70	-2.88
			[0.005]	[0.007]	[0.004]
AR2-Test			-1.43	-1.43	-1.39
			[0.152]	[0.152]	[0.166]
Sargan-Test			13.68	10.18	10.98
			[0.550]	[0.808]	[0.754]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

To assure the soundness of AB estimation the coefficient on the LDV should lie within the range, or nearby the coefficient in OLS (upward biased) and fixed effects (downward biased) (Roodman, 2009). This is precisely the case in our analysis. Further, both the AR2-test and Sargan-test indicate that our results are econometrically sound, as argued in section 4. We further employ different lags of our innovation variable as potential regressors in line with similar work (Wang et al., 2012). However, we find that only the first lag is significant, which is both plausible from a theoretical perspective (see section 2) and the results on our other relevant variables do not change significantly from only including the first lag. Hence, we will continue our further analysis by using the first lag of the innovation variable in our model.

Our findings within the baseline model indicate that EI, GDP and Energy have a significant impact on the carbon dioxide emissions. Our main variable of interest, i.e. EI, exerts a reducing effect on carbon dioxide emissions. The coefficient lies at ~ -0.01, indicating that a 1% increase in environmentally innovative activity is associated with a 0.01% decrease in emissions.

The results concerning Energy and GDP show that both affect carbon dioxide emissions positively, indicating that increases in either variable cause emissions to rise. With regard to the scale aspect that these variables capture, these results are not surprising (Carattini et al., 2015). However, it is obvious that the effect of Energy is much larger, roughly three to four times as high as the effect of GDP. This indicates that Energy is more strongly related to carbon dioxide emissions, as a 1% increase in Energy raises emissions by 0.5%. Given the direct linkage of energy consumption with emissions due to the burning of fossil fuels, this is not surprising (Carattini et al., 2015). GDP then captures only a residual part of the scale effect as a major aspect of growing GDP can be an increase in energy consumption. However, our results still indicate that GDP affects emissions with a coefficient of ~ 0.15, meaning a 1% increase in GDP to raise emissions by 0.15% beyond the effect of increased energy consumption.

We now turn to our estimations with inclusion of further control variables. As outlined in the data section we consider Renewable Energy, FDI, Trade Openness, Urban Population and the Industrial Intensity as control variables. We expect the following relationships:

Renewable Energy (-): The share of renewables in the energy supply structure should influence carbon dioxide emissions in a negative way, as the fossil fuel burning for energy is a strong direct link to emissions and the effect of the energy supply structure should not be partially captured by any other variable.

FDI (-): We consider FDI as a robustness check on our innovation variable, as we basically include only domestic green innovation into our model. A domestic innovative basis has been considered to be pivotal, as domestic innovation is directly related with regulatory pressure and the need for sustainable governance (Costantini et al., 2017; Popp, 2006). Yet, especially in transition economies foreign direct investment may lead to the spilling over of new and advanced technologies, potentially raising the efficiency of production. Thus, we consider FDI relevant to capture this potential technological upgrading. We expect FDI to reflect import of foreign technology, improving the technological level and thus reducing emissions.

Trade Openness (-): Trade openness has been thoroughly used in the relevant literature, especially in the context of carbon leakage. Given our data, we cannot control for carbon leakage in our measure of carbon dioxide emissions. Hence, we consider trade openness, due to being related with trade liberalization, specialization, and displacement of polluting activities and technology transfer (Carattini et al., 2015). Therefore, we expect trade openness to reduce carbon dioxide emissions.

Industrial Intensity (±): The economic structure is considered a relevant determinant of emissions (Carattini et al., 2015), as the industrial sector is generally understood to be more environmentally intensive (Carattini et al., 2015; Weisz et al., 2006). As in our setting the main relation may be mediated via Energy, we also expect that the Industrial intensity does not exert a relevant effect.

Urban population (±): The structure of the population is considered to reflect differences in lifestyle, with urban population living under a different socio-metabolic mode (Shao et al., 2017). However, given the inclusion of energy consumption we expect this variable to not exert a significant impact.

The results of the inclusion of our controls is reported in Table 2. The inclusion of Renewable Energy in the model shows a relevant impact. This inclusion leaves the effects and size of green innovation and energy consumption unchanged. While the size of the coefficient of GDP remains stable, it loses its significance. Renewable Energy shows by far the largest coefficient, being significant at the 1% level. The coefficient lies at ~ -1.8. As expected a higher share of renewable energy in the energy supply structure decreases the amount of emissions. Given that we had to include Renewable Energy in first differences, due to its non-stationarity in levels, leads to the following interpretation. The coefficient shows that a one percentage point increase in the growth of the renewable energy share leads to a 1.8% reduction of carbon dioxide emissions. It is interesting that the coefficient on EI remains significant and of a similar magnitude, indicating that the effect of EI is beyond the increase of renewable energy in the energy structure of an economy.

None of our further control variables shows to be significant. As argued above, however, this seems reasonable in all cases, including the share of the industrial sector as energy consumption may mediate the emission raising effect of this variable. Trade openness and urban population also do not show any significant impact. The inclusion of FDI seems most relevant, to check the robustness of the impact of green innovation. We included FDI with one lag, as we expect a time-lag from the financial investment to the actual implementation of new technology resulting in environmental effects. FDI is insignificant and does not take away the effect of EI. For further testing we combine trade openness and FDI in one specification to secure that we separate the effects of technology import and carbon leakage. The magnitude and significance of EI remains unchanged, while both trade openness and FDI remain insignificant.

Table 2: Inclusion of controls into baseline model

	(1)	(2)	(3)	(4)	(5)	(6)
Model	AB	AB	AB	AB	AB	AB
Dep. Var.	CO_2	CO_2	CO_2	CO_2	CO_2	CO_2
L1. CO_2	0.645***	0.571***	0.601***	0.608***	0.514***	0. 579***
	(0.148)	(0.140)	(0.140)	(0.137)	(0.167)	(0. 170)
L1. Environmental Innovation	-0.0109**	-0.0132**	-0.0132**	-0.0131**	-0.0131**	-0.0104**
	(0.00498)	(0.00590)	(0.00582)	(0.00601)	(0.00566)	(0.0050)
Energy	0.425**	0.512***	0.482**	0.475**	0.547**	0.474**
	(0.183)	(0.179)	(0.176)	(0.173)	(0.203)	(0.206)
GDP	0.103	0.129*	0.127*	0.125	0.157**	0.112
	(0.0614)	(0.0735)	(0.0746)	(0.0792)	(0.0755)	(0.075)
D1. Renewable Energy	-1.749***					-1.640***
	(0.336)					(0.308)
Trade Openness		0.00749				0.0019
		(0.0185)				(0.024)
Urban Population			-0.0218			
			(0.176)			
Industrial intensity				0.0214		
				(0.0937)		
L1. FDI					-0.00456	-0.0061
					(0.00372)	(0.0038)
Time-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	550	548	550	550	522	522
No. of Countries	27	27	27	27	27	27
AR1-Test	-2.80	-2.80	-2.85	-2.88	-2.64	-2.65
	[0.005]	[0.005]	[0.004]	[0.004]	[0.008]	[0.008]
AR2-Test	-0.19	-1.42	-1.41	-1.41	-1.51	-0.41
	[0.848]	[0.157]	[0.159]	[0.159]	[0.130]	[0.682]
Sargan-Test	16.11	13.79	13.67	13.35	13.31	17.15
	[0.374]	[0.541]	[0.550]	[0.576]	[0.579]	[0.310]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

The obtained results cause us to include renewable energy into our further modelling to avoid misspecification. Thus, we will now continue with this model to check the robustness of our results.

3.5.2 Robustness Checks

We now continue to analyze our main model, including green innovation, GDP, energy consumption, and the share of renewable energy more indepth. At first, we will conduct a variety of classic robustness checks, by restricting our time-period to the time after the Kyoto Protocol, excluding the years of the financial crises 2008 and 2009, and excluding the three smallest countries of the European Union with less than one million inhabitants, namely Luxembourg, Malta and Cyprus (see Table 3). Then we will explore our main explanatory variable more specifically by testing an alternative environmental innovation patent search strategy, and compare the results obtained for green innovation with the results for overall innovation and non-green innovation to verify whether EI exerts a unique environmental effect. Lastly, we will explore country heterogeneity concerning the effect of EI.

Table 3: Robustness checks by restricting the sample

	(1)	(2)	(3)
Model	AB	AB	AB
Dep. Var.	CO_2	CO_2	CO_2
Restriction	Year>1997	Excl. 2008 & 2009	Excl. MT, LU, CY
L1. CO_2	0.537***	0.604***	0.667***
	(0.165)	(0.138)	(0.124)
L1. Environmental Innovation	-0.0115**	-0.0124**	-0.0103*
	(0.00431)	(0.00544)	(0.00542)
Energy	0.520**	0.482***	0.376**
	(0.231)	(0.163)	(0.153)
GDP	0.174**	0.0841	0.0993
	(0.0679)	(0.0547)	(0.0792)
D1. Renewable Energy	-1.452***	-1.784***	-1.762***
	(0.315)	(0.380)	(0.340)
Time-effects	Yes	Yes	Yes
Observations	417	496	492
No. of Countries	27	27	24
AR1-Test	-2.19	-2.75	-2.84
	[0.029]	[0.006]	[0.005]
AR2-Test	-0.06	-0.01	-0.24
	[0.949]	[0.990]	[0.807]
Sargan-Test	19.18	17.99	17.41
	[0.206]	[0.263]	[0.295]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

The results in Table 3 show the robustness of our main results on all variables, except for GDP. While GDP turned insignificant in our regular sample it turns significant at the 5% level when focusing on the time after the Kyoto Protocol.

Table 4: Robustness concerning green patent search strategy

	(1)	(2)	(3)	(4)
Model	FE DK	AB	FE DK	AB
Dep. Var.	CO_2	CO_2	CO_2	CO_2
EI search strategy	Green Inventory	Green Inventory	Green Inventory + OECD EnvTech	Green Inventory + OECD EnvTech
L1. CO_2	0.405***	0.647***	0.403***	0.645***
	(0.0552)	(0.144)	(0.0560)	(0.148)
L1. Environmental Innovation (GI)	-0.0120**	-0.0123**		
	(0.00488)	(0.00526)		
L1. Environmental Innovation (GI + OECD)			-0.0105**	-0.0109**
			(0.00445)	(0.00498)
Energy	0.672***	0.423**	0.672***	0.425**
	(0.0692)	(0.178)	(0.0693)	(0.183)
GDP	0.108***	0.107*	0.106***	0.103
	(0.0345)	(0.0610)	(0.0349)	(0.0614)
D1. Renewable Energy	-1.369***	-1.762***	-1.359***	-1.749***
	(0.111)	(0.337)	(0.113)	(0.336)
Time-effects	Yes	Yes	Yes	Yes
Observations	574	547	577	550
No. of Countries	27	27	27	27
R-squared	0.8957		0.8946	
AR1-Test		-2.80 [0.005]		-2.80 [0.005]
AR2-Test		-0.21 [0.836]		-0.19 [0.848]
Sargan-Test		15.77 [0.397]		16.11 [0.374]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Table 4 shows the results of using different patent search strategies. As our main variable we have merged the OECD EnvTech (OECD) with the Green Inventory (GI) to obtain a comprehensive list of green technologies. Defining EI narrowly may reduce the potential issue of including irrelevant patents, which is considered to be more severe for potential biases (Lanjouw and Mody, 1996).[48] Our comprehensive list of EI avoids the danger of not capturing all green technologies, which would lead to only a result for the analyzed subgroup of green technologies. However, including too many technologies as green ones may lead to biased results. The results might be downward biased if the included technologies have no similar

[48] Given that our model calculates in first differences, having too low absolute numbers is not too much of an issue, as the change rates are relevant for obtaining results.

effect as the green technologies on our dependent variable (Wurlod and Noailly, 2016). Since the WIPO Green Inventory (GI) is considered to be narrower (Ghisetti and Quatraro, 2017) we choose for a robustness check to only include the GI IPC codes. When using the Green Inventory the coefficient, indeed, gets a little larger in magnitude, remaining significant at the 5% level.

Given the political pursuit of green innovation (European Commission, 2011), we are interested in whether the shift from non-green to green technologies is actually leading to an improvement of environmental performance. Therefore, we now use Total Innovation and non-environmental innovation besides EI. The results of these specifications are reported in Table 5. As innovation is generally about improving efficiency, and given the fact that regular innovations may also provide environmental benefits (Kemp and Pearson, 2007) we test for total innovation first. However, the coefficient stays insignificant, not showing any reductional impact of general innovative activity. Next, we test for both our stricter definition of EI (GI) and our comprehensive definition (GI + OECD). First, for reference purposes, only the inclusion of EI, and then a specification including both EI and non-green innovations are displayed. Thus, we avoid potential omission issues coming along with excluding technologies. The results show that EI maintains its reducing effect on emissions when we include non-green innovation. Non-green innovations on the other hand do not exert any significant impact on emissions. This is in line with what we expected. General innovations, which shall improve efficiency and result in economic benefits are not equally expected to reduce emissions, as the reduction of emissions is largely about reducing negative externalities. However, we also do not find that regular innovations increase the amount of emissions, e.g. by facilitating the use of non-green technologies. These results are also not sensitive to the choice of our EI definition. We consider this as a strong robustness check, that we have identified an actual effect of EI. We have used both a narrower and a comprehensive definition of EI with very similar effects, to avoid the issue of having selected too few or too many patents. As we have shown that neither total innovation nor non-green innovation exert an effect, we can assure that EI has a unique effect on emissions.

Table 5: Comparison of Total, Green and Non-green innovation

	(1)	(2)	(3)	(4)	(5)
Model	AB	AB	AB	AB	AB
Dep. Var.	CO_2	CO_2	CO_2	CO_2	CO_2
Patent search strategy	All patents	Green patents (Green Inventory)	Green and Nongreen patents (Green Inventory)	Green patents (Green Inventory + EnvTech)	Green and Nongreen patents (Green Inventory + EnvTech)
L1. CO_2	0.778***	0.647***	0.670***	0.645***	0.663***
	(0.128)	(0.144)	(0.162)	(0.148)	(0.166)
L1. Total Innovation	-0.000864				
	(0.00824)				
L1. Environmental Innovation (GI)		-0.0123**	-0.0113**		
		(0.00526)	(0.00542)		
L1. Non-Environmental Innovation (GI)			0.00301		
			(0.00944)		
L1. Environmental Innovation (GI+OECD)				-0.0109**	-0.0102**
				(0.00498)	(0.00470)
L1. Non-Environmental Innovation (GI+OECD)					0.00265
					(0.00893)
Energy	0.275*	0.423**	0.404*	0.425**	0.411*
	(0.156)	(0.178)	(0.201)	(0.183)	(0.207)
GDP	0.0747	0.107*	0.0608	0.103	0.0557
	(0.0770)	(0.0610)	(0.0847)	(0.0614)	(0.0868)
D1. Renewable Energy	-1.839***	-1.762***	-1.812***	-1.749***	-1.792***
	(0.405)	(0.337)	(0.340)	(0.336)	(0.337)
Time-effects	Yes	Yes	Yes	Yes	Yes
Observations	582	547	543	550	546
No. of Countries	27	27	27	27	27
AR1-Test	-2.79	-2.80	-2.78	-2.80	-2.77
	[0.005]	[0.005]	[0.005]	[0.005]	[0.006]
AR2-Test	0.41	-0.21	-0.11	-0.19	-0.10
	[0.680]	[0.836]	[0.914]	[0.848]	[0.917]
Sargan-Test	11.15	15.77	15.94	16.11	16.74
	[0.742]	[0.397]	[0.386]	[0.374]	[0.335]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Although the development of technologies is likely related with diffusion, differences of environmental effects of EI between countries may arise from a variety of aspects. Amongst other factors structural differences or the presence of absorptive capacity (Keller, 1996) to use technologies may cause the effects of EI, measured by patent applications, not to be homogenous across countries. While technology development in companies may be driven by international programs and competition the national effects could be moderated, for example, by preferences of citizens, which may be dependent on the developmental level of a country (Stern, 2004).

Hence, we now continue by providing analyses based on these considerations in multiple ways. First, we exclude countries based on their average GDP per capita during our time-period (1992 to 2014). Thereby we aim to evaluate whether the developmental level of a country influences EI effects. Next, we exclude countries which have a strong domestic availability of fossil resources. To identify these countries we rely on material flow data (UNEP, 2016)[49] to construct an indicator of `domestic resource dependency` (DRD) meaning the share of fossil materials extracted in the home-country versus all fossil materials entering the socio-economic system (Fischer-Kowalski et al., 2011; Weisz et al., 2006). Lastly, we will show how the exclusion of individual countries affects the coefficient of EI.

When excluding countries based on their developmental level the results show a clear tendency (compare Table 6). When excluding the three richest countries, namely Denmark (DK), Luxembourg (LU), and Ireland (IE), the coefficient of EI changes from -0.0109 to – 0.00797, indicating a reduced negative effect of EI. The opposite is the case when excluding the three poorest countries, Bulgaria (BG), Romania (RO), and Latvia (LV). The coefficient increases in magnitude to -0.0143. This tendency holds when excluding the seven richest and poorest countries. Excluding the seven richest countries[50] causes EI to lose its significance, with the coefficient dropping in magnitude to -0.00615, while for the seven poorest countries[51] the coefficient increases further to -0.0164. These results can be seen as an indication that within the richer countries the effect of EI is stronger than in the EU-27 average, while poorer countries seem to have a weaker negative effect. However, these results motivate the idea that EI effects seem not to be homogenous across countries but could depend on the developmental level, with rich countries profiting more from domestic green innovation. This could be interpreted in various ways. Explanations could range from issues with absorptive capacity in less developed countries to the stronger diffusion of green technologies in developed economies due to e.g. preferences and purchasing power of the citizens. Further, for less developed economies domestic innovation may be less important compared to imported technologies, while

[49] Material flow data has been extracted from the Global Material Flows Database publicly available at https://www.resourcepanel.org/global-material-flows-database. We derived data on the so-called Direct Material Input (DMI) which is equivalent to adding-up materials extracted domestically and materials which were imported.
[50] Which are Denmark (DK), Luxembourg (LU), Ireland (IE), Netherlands (NL), Sweden (SE), Austria (AT) and the United Kingdom (UK).
[51] Which are Bulgaria (BG), Romania (RO), Latvia (LV), Poland (PL), Lithuania (LT), Estonia (EE) and Slovakia (SK).

developed economies more heavily rely on domestically provided green technologies (Lema and Lema, 2012).

Table 6: Robustness of Results to systematic exclusion of country groups

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Criterion	EU27	3 Richest	3 Poorest	7 Richest	7 Poorest	DRD > 80%	DRD > 75%
Model Dep. Var.	AB CO_2	AB CO_2	AB CO_2	AB CO_2	AB CO_2	AB CO_2	AB CO_2
Countries excl.	None	DK & LU & IE	BG & RO & LV	DK & LU & IE & NL & SE & AT & UK	BG & RO & LV & PL & LT & EE & SK	EE & PL	EE & PL & CZ & RO
L1. CO_2	0.645***	0.646***	0.590***	0.681***	0.389**	0.645***	0.664***
	(0.148)	(0.141)	(0.159)	(0.161)	(0.172)	(0.143)	(0.137)
L1. Environmental Innovation	-0.0109**	-0.00797*	-0.0143**	-0.00615	-0.0164**	-0.0147**	-0.0197***
	(0.00498)	(0.00410)	(0.00612)	(0.00396)	(0.00674)	(0.00582)	(0.00630)
Energy	0.425**	0.404**	0.475**	0.374*	0.867***	0.412**	0.391**
	(0.183)	(0.162)	(0.219)	(0.187)	(0.279)	(0.182)	(0.178)
GDP	0.103	0.0984	0.126	0.107**	-0.102	0.111*	0.137**
	(0.0614)	(0.0625)	(0.0882)	(0.0501)	(0.195)	(0.0590)	(0.0560)
D1. Renewable Energy	-1.749***	-1.632***	-1.613***	-1.918***	-1.366***	-1.728***	-1.684***
	(0.336)	(0.296)	(0.348)	(0.358)	(0.294)	(0.326)	(0.373)
Time-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	550	484	501	396	430	512	473
No. of Countries	27	24	24	20	20	25	23
AR1-Test	-2.80 [0.005]	-2.78 [0.005]	-2.59 [0.010]	-2.58 [0.010]	-2.05 [0.041]	-2.80 [0.005]	-2.80 [0.005]
AR2-Test	-0.19 [0.848]	-0.21 [0.836]	0.55 [0.579]	-0.45 [0.650]	0.69 [0.491]	-0.02 [0.984]	0.01 [0.989]
Sargan-Test	16.11 [0.374]	14.67 [0.475]	18.57 [0.234]	15.48 [0.417]	12.53 [0.639]	14.38 [0.497]	18.28 [0.248]

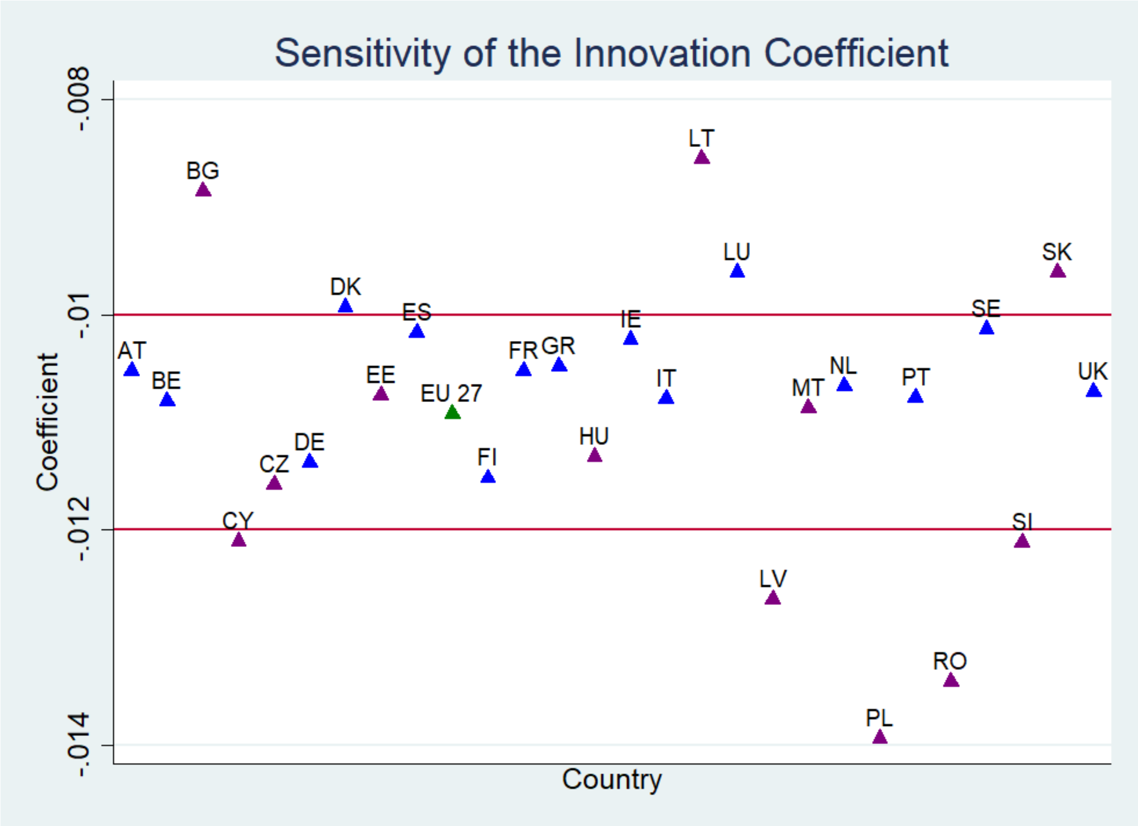
Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

Another aspect is the effect of countries which have a high-level of DRD for fossil fuels. High levels of fossil DRD could relate to structural barriers impeding the establishment of more sustainable technological systems. Our results indicate that countries with a higher level of DRD have a less negative effect of EI on emissions. Estonia (EE) and Poland (PL) have the highest levels with more than 80% of used fossils being extracted in the country itself.[52] Excluding Estonia and Poland leads to an increase of the coefficient to -0.0147. Romania (RO) and the Czech Republic (CZ) follow with more than 75% of fossils extracted domestically. Without these countries the coefficient of EI increases again, almost reaching -0.02. Hence, the

[52] On average during our observed period.

exclusion of countries based on this criterion causes a more pronounced change of the EI effect than excluding countries based on their developmental level.

As a final check we drop each country individually and report the coefficient of EI. As can be seen in Figure 1 below most countries do not cause substantial changes. However, Poland (PL), Romania (RO), Latvia (LV), Cyprus (CY), and Slovenia (SI) cause a strong decrease in coefficient size, reaching -0.012 and less. Poland causes the strongest decrease of the coefficient reaching almost -0.014. The strongest increases in coefficient size are caused by excluding Lithuania (LT) where the coefficient changes to -0.0085, followed by Bulgaria (BG, -0.0089), Slovakia (SK, -0.0096), and Luxembourg (LU, -0.0096). Two aspects are striking in this graph. On the one hand, with Poland, Romania, and Czechia three of the four countries with very high DRD of fossils are also among the six countries which individually lead to the strongest decrease in the coefficient size. Further, both the countries leading to the strongest increase but also decrease of the coefficient belong to the non EU-15 countries. EU-15 countries do not cause such strong changes in the coefficient size. Hence, this could be interpreted in the way that among less developed economies the effects of EI on emissions seem to be much more heterogeneous than among the higher developed economies, which also share a longer common institutional history, due to the European Union framework.



Source: Own calculations.

Figure 1: Development of the Coefficient of EI. Individual countries were dropped and the coefficient reported. Blue triangles refer to EU-15 countries. Purple triangles refer to non-EU-15 countries. The green triangle shows the baseline model with all 27 countries. The country codes indicate the country omitted. The red lines mark deviations of the coefficient which surpass an increase or decrease of the coefficient by ~0.001 or more, compared to the result of EU-27.

3.6 Discussion and Conclusion

Green technologies are considered as a practical and realistic means to encounter global warming and environmental issues. In this paper we aimed to identify the effect of green technologies on carbon dioxide emissions in European countries. Using a dynamic panel data model we analyzed the EU-27 countries between 1992 and 2014. To the best of our knowledge we thus provide the first cross-country analysis at the national level looking at the environmental effects of EI.

Past studies have shown that at a sectoral level the contribution of EI to reductions of emissions and energy usage is given (Carrión-Flores and Innes, 2010; Costantini et al., 2017; Ghisetti and Quatraro, 2017; Wurlod and Noailly, 2016). At the regional-national level, however, the results are more divergent, dependent on the specific empirical setting (Wang et al., 2012; Weina et al., 2016; Zhang et al., 2017).

Our findings indicate that EI does have a reducing effect on emissions. This effect is unique to EI, as general innovation is not associated with emission reduction. The developmental stage of countries seems to play a role for the magnitude of the EI effect, as our results suggest that within higher developed economies EI more strongly contributed to emission reduction than in less developed countries. For the latter, we find a higher level of heterogeneity as all countries that strongly influence the EI coefficient size belong to the non-EU-15 countries. Furthermore, we find that countries with a high domestic availability of fossil fuels seem to be less receptive towards the reducing effects of EI.

Our further findings show that Energy and GDP are associated with increases in carbon dioxide emissions, whereby Energy has a larger effect. However, the energy supply structure has a strong influence on our dependent variable. We find that increases in the growth of renewable energy utilization are associated with disproportionally high decreases in emissions. Hence, a strong reducing effect of EI may lie in the expansion of renewable energy usage. Given the systemic nature of changes in the energy supply system it seems difficult to appropriately and directly capture the effect of EI on renewable energy expansion (Popp et al., 2011). However, EI is obviously related to reducing the energy unit costs of renewable energy, thus supporting the further diffusion of renewable energy. This likely strong reducing effect of EI cannot be sufficiently measured via our innovation variable.

Further research is needed to consolidate our findings and to clarify open questions. Firstly, if emissions occur in another country, they are not captured as CO_2 emissions in our dependent variable which is due to the territorial principle of accounting CO_2. Interesting insights could be provided by looking at similar contexts using other data, for example including upstream requirements in CO_2 data.[53] Secondly, as a fundamental concern a national system boundary should be questioned when assessing technology effects, given that these are of a holistic nature and often go beyond direct and short-term empirically accessible impacts (Hepburn et al., 2018). Lastly, given differences in EI effects across countries, an interesting new line of research would be to conduct in-depth research on EI effects in different countries and the role which countries' specificities play.

[53] This is usually attempted via global multiregional input-output tables (MRIO).

At a global scale, despite strong improvements in emission efficiency, a strong decline in absolute levels has not yet been observed. Thus, the necessary reduction in CO_2 intensity to stay within the absolute limits (Rockström et al., 2009) for emissions is far from being reached by technological development. Further, there are fundamental concerns on the limits of improving the efficiency of economic activity given inevitable limits (Georgescu-Roegen, 1971; Meadows et al., 1972; Schramski et al., 2015). The solution approach towards encountering environmental degradation needs to be a holistic one as the effects of technologies are of a holistic nature, too. Pure reliance and concentration on technological progress is not sufficient, but a holistic reform and transformation of all fundamental system aspects is needed. To face future environmental problems technological innovation must be embedded and used as a supplementary tool within a systemic transformation.

Appendix

Table A1: Descriptive statistics[54]

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max	Source
CO_2 Emissions	Thousand Metric Tons (TMT)	621	142108.6	190913.3	2024.184	891975.4	Carbon Dioxide Information Analysis Centre (CDIAC)
Energy Consumption	Thousand Tons of Oil Equivalent (TTOE)	621	63760.06	85075.38	621.3999	352856.9	Eurostat
GDP	Billions of Euro[55]	621	401.9651	627.0884	3.168	2601.824	European Regional Database (ERD)
Environmental Patents (GI + OECD, EPO, Applicant, Whole counting)	Count	621	353.6006	901.8494	0	6639	PATSTAT 2017b
Environmental Patents (GI, EPO, Applicant, Whole counting)	Count	621	269.9469	664.0224	0	4863	PATSTAT 2017b
Non-Environmental Patents (GI + OECD, EPO, Applicant, Whole counting)	Count	621	1583.559	3702.332	0	23214	PATSTAT 2017b

Table A1 continues

[54] For the used sample in initial units for the years 1992 to 2014.
[55] In constant 2005 prices.

Non-Environmental Patents (GI, EPO, Applicant, Whole counting)	Count	621	1667.213	3936.98	0	24806	PATSTAT 2017b
Total Patents (EPO, Applicant, Whole counting)	Count	621	1937.159	4591.022	0	28693	PATSTAT 2017b
Renewable Energy: Share of GIEC	Share	621	.0937323	.0866182	0	.3715844	Eurostat
Industrial Intensity:[56] Sector Share in Gross Value Added	Share	621	.276535	.0598955	.1141474	.4698775	European Regional Database (ERD)
Trade Openness[57]	Share	609	1.047754	.5871905	.350209	3.822915	World Bank
Urban Population	Share	621	.7197536	.1177277	.4913	.97818	World Bank
Foreign Direct Investment (FDI): Net inflows share of GDP	Share	586	.089589	.3331599	-.5832288	4.517155	World Bank

[56] Share of the Industry Sector in Gross Value Added.
[57] Trade Openness is equivalent to the sum of Imports/GDP and Exports/GDP.

Table A2: Unit Roots

	Fisher ADF Inv. X2	Fisher ADF Inv. N	Fisher ADF Inv. L	Fisher ADF M. Inv. X2
CO2 Emissions	122.1942 [0.0000]	-4.9443 [0.0000]	-5.1288 [0.0000]	6.5620 [0.0000]
Energy Consumption	166.1549 [0.0000]	-7.9549 [0.0000]	-8.2985 [0.0000]	10.7921 [0.0000]
GDP	187.0374 [0.0000]	-9.2752 [0.0000]	-9.7489 [0.0000]	12.8015 [0.0000]
Environmental Patents (GI + OECD)	144.4375 [0.0000]	-7.4048 [0.0000]	-7.3532 [0.0000]	8.7024 [0.0000]
Environmental Patents (GI)	146.2144 [0.0000]	-7.5126 [0.0000]	-7.4692 [0.0000]	8.8733 [0.0000]
Non-Environmental Patents (GI + OECD)	187.4035 [0.0000]	-9.1537 [0.0000]	-9.7391 [0.0000]	12.8368 [0.0000]
Non-Environmental Patents (GI)	190.0388 [0.0000]	-9.2292 [0.0000]	-9.8733 [0.0000]	13.0903 [0.0000]
Total Patents	174.7351 [0.0000]	-8.6519 [0.0000]	-9.0280 [0.0000]	11.6177 [0.0000]
Renewable Energy	38.6815 [0.9425]	4.0921 [1.0000]	4.5691 [1.0000]	-1.4740 [0.9298]
Δ Renewable Energy	274.5258 [0.0000]	-12.115 [0.0000]	-14.324 [0.0000]	21.2201 [0.0000]
Industrial Intensity	121.8800 [0.0000]	-4.8743 [0.0000]	-5.1821 [0.0000]	6.5318 [0.0000]
Trade Openness	124.6579 [0.0000]	-6.1107 [0.0000]	-6.0688 [0.0000]	6.7991 [0.0000]
Urban Population	100.7640 [0.0001]	-3.6333 [0.0001]	-3.7019 [0.0002]	4.4999 [0.0000]
FDI	227.1148 [0.0000]	-11.002 [0.0000]	-12.004 [0.0000]	16.6580 [0.0000]

Variables used are in logarithm or share.

Fisher-ADF: *The Fisher-type unit-root tests are based on augmented Dickey–Fuller (Fisher-ADF) tests with drift and one lag; the null hypothesis is that "all panels contain unit-roots"; the test does not require a balanced panel. Statistics and respective p-values (in square brackets) are reported for each type of Fisher test: inverse chi-squared, inverse normal, inverse logit and modified inverse chi-squared.*

Δ is the first difference operator*.*

A3: Descriptives on emissions and patents

We will now explore in more detail our data for our sample period 1992 to 2014. Concerning CO_2 emissions at a country level, the largest emitters are Germany, the United Kingdom (UK), Italy, and France. Germany is by far the largest emitter in absolute terms with a mean value between 1992 and 2014 of ~812,500 thousand metric tons (TMT) followed by the UK with ~518,000 TMT on average. The smallest emitter of CO_2 is Malta with ~2,430 TMT followed by Cyprus with ~6,800 TMT. Luxembourg and Latvia also remain below the 10,000 TMT threshold. The largest and smallest values across the whole sample also occur within the largest and smallest emitter countries. In 1992 both the largest value (~892,000 TMT in Germany) and the smallest value (~2,000 TMT in Malta) are observed. It is apparent that the absolute levels of CO_2 emissions largely correspond with the size of the countries and their level of economic development, as Germany (~2.3 trillion), the UK (~1.8 trillion), France (~1.7 trillion), and Italy (~1.4 trillion) have the largest mean values of GDP, while Malta(~5 billion) followed by Estonia (~9 billion), Latvia (~12 billion), and Cyprus (~14 billion) have the lowest mean values of GDP. Hence, it may be more informative to look at a relative measure accounting for the economic size of a country to get an impression of the environmental impact of the countries. For this purpose we compute a measure of environmental intensity, namely the amount of CO_2 emissions (in TMT) per unit of GDP (in billion). There are other countries at the top and bottom of the ranking. Five countries, namely Bulgaria (~7.7), Estonia (~7.6), Poland (~7.2), Romania (~7.2), and the Czech Republic (~7.1) caused on average more than 7 TMT CO_2 per billion GDP. The most environmentally friendly countries on the flipside are Sweden (~5.2), France (~5.4), Denmark (~5.5), and Austria (~5.6). The highest intensity can be found in Bulgaria in 1993 with 8.29 TMT CO_2 per billion GDP, while Sweden provides the lowest value in 2014 with only 4.79 TMT CO_2 per billion GDP.

Figure A3 below shows the development of all our key variables over the whole range of time observed. EI[58] as well as GDP are increasing over this period, with recognizable drops. CO_2 is rather constant and decreasing towards the end of our time-period. The CO_2 intensity of GDP is consequently decreasing. All variables were summed up for all countries in our dataset.

[58] We used the patent counts of our main explanatory variable, namely EI defined by combining the WIPO Green Inventory and the OECD EnvTech.

The time series are normed to the year 2003, where all variables are equal to 1. Hence, it is visible that across EU-27 countries the CO_2 intensity has decreased from more than 1.2 times of the 2003 value in the early nineties to less than 0.8 times of the 2003 value in 2014.

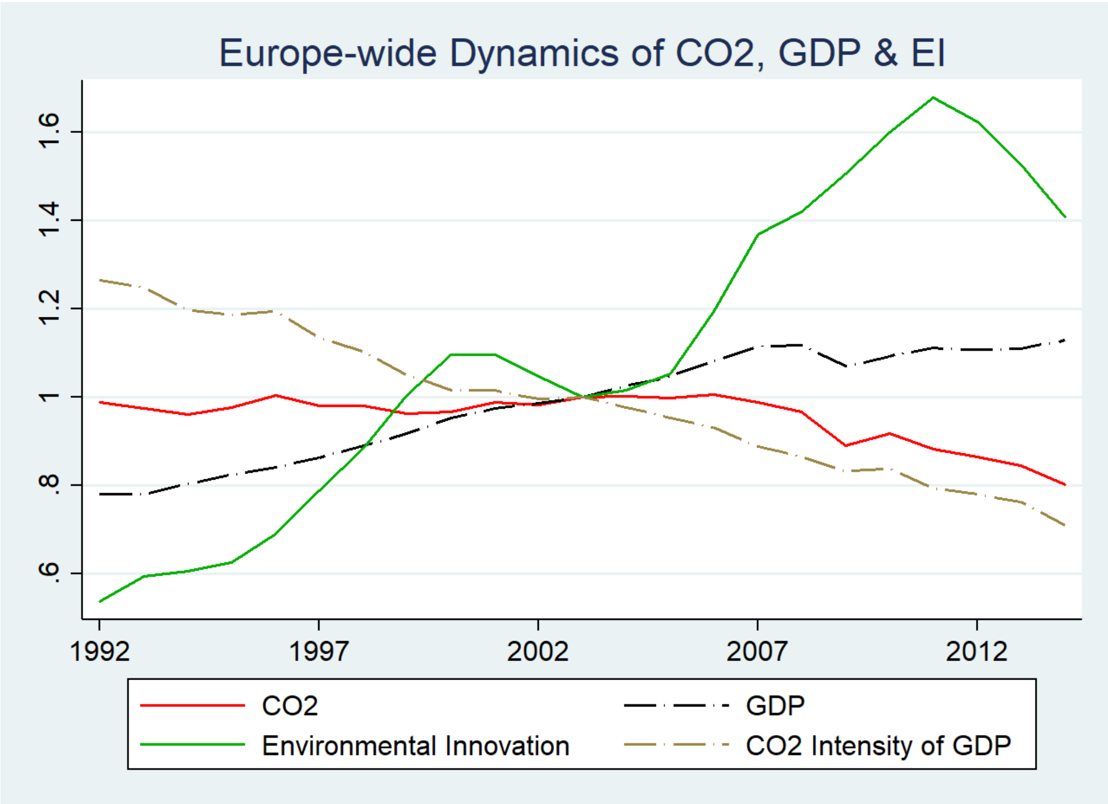


Figure A3: Aggregate Dynamics of key variables in the EU-27 countries between 1992 and 2014. All variables are normed by their 2003 value.

Concerning our main explanatory variable of interest, i.e. green patenting, we find the following patterns: The largest mean values of green patents per year are found for Germany (4,397) and France (1,345), followed by the UK (834), the Netherlands (700), and then Italy (514). The smallest average values of green patent applications per year are found for Lithuania (2.26) and Latvia (2.39) followed by Bulgaria (3.52), Malta (3.56), and Romania (3.7). Again, these numbers are strongly bound to the overall size of the respective economy. A completely different picture appears when computing the share of green patent applications among all patent applications. In these terms, Slovakia (0.29), Lithuania (0.27) and Bulgaria (0.27) have the highest share of green patents, while Latvia (0.12), Italy (0.14) and Sweden (0.14) show the lowest share of green patent applications, according to our classification of environmental technologies. However, the numbers above may be strongly driven by the different magnitudes in innovative activity and patterns over time. Within the EU-15 countries the mean value of patent applications is about 60 times higher than for the eastern European countries. Hence, while the share of green patents ranges between 0 and 1 for eastern European countries, it ranges between 0.06 and 0.53 in the EU-15. Further, even within the EU-15 these extreme values are both found for Greece in 1996 respective 1993. For a large mature economy, namely Germany, the share of green patents ranges between 16 and 24% throughout the whole time period.

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Chapter 4

About the Relationship Between Green Technology and Material Usage

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Abstract

This paper examines the effects of environmental innovation on material usage, using Direct Material Input (DMI) and Raw Material Input (RMI) as indicators of material usage. The analysis is conducted on European Union countries for the years 1990 to 2012. We utilize the Generalized Method of Moments in a dynamic panel setting. Based on patent data, we construct green knowledge stocks for specific technological domains. We find that the effect of environmental innovation differs between subdomains. Innovation in the areas of energy efficiency, and recycling and reuse is found to reduce material usage. For alternative energy production, transportation, production or processing of goods, and general green innovation no significant effect is found. We observe a distinct reducing effect of some environmental innovation areas when compared with overall innovation. The technology effects are similar for RMI and DMI. The results are discussed from the perspective of literature on the environmental effects of environmental innovation, and literature on decoupling.

Keywords: Decoupling ® Dynamic Panel ® Environmental Innovation ® Material Flows ® Patent Data ® Sustainable Development

JEL Classification: Q01; Q55; Q56; Q58

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4.1 Introduction

Sustainable Development (SD) has become an important item on the global political agenda, reflected inter alia in the UN 2030 Agenda for Sustainable Development (United Nations, 2015). However, unimpressed by resource scarcities or the danger of climate change, unfettered economic growth remains the focal point of economists and policy makers. Even the Agenda for Sustainable Development acknowledges economic growth as an integral part of the equation. Increased economic activity has undoubtedly caused a dramatic increase in environmental pressures. Even before a fundamental questioning of the growth paradigm, the consequences of economic activity on the environment are obvious (Rockström et al., 2009; Schramski et al., 2015).

Innovation is a key force for offsetting scale effects to align economic development with environmental sustainability. Achieving this forceful decoupling of economic growth from resource use and the associated environmental impacts, crucially depends on technological improvements reducing pressure stemming from production and consumption (Popp et al., 2010). This assumption is formulated more clearly in the IPAT hypothesis, which states that environmental impact (I) is not just proportional to the scale of human population (P), but depends on the level of affluence (A) and specific technology choices (T) (Steinberger et al., 2010; Weina et al., 2016).

Decoupling economic development from its environmental impact is ultimately about increasing the productivity by which environmental resources are transformed into economic goods and services (Baptist and Hepburn, 2013). Some studies claim that Europe has already achieved a high level of decoupling between economic growth and material use, at least in relative terms (Moll et al., 2005; Voet et al., 2005). These claims are supported by a conviction that has begun to influence policy (OECD, 2011). These endeavors are reflected in a variety of political programs and initiatives, such as the Raw Materials Initiative (European Commission, 2008), the Europe 2020 strategy declaring a resource efficient Europe as one of the seven flagship initiatives (European Commission, 2010), or the Roadmap to a Resource Efficient Europe (European Commission, 2011a). These efforts strive towards the concept of a circular economy (European Commission, 2015), although limits to circularity are inevitable (Cullen, 2017). The shift to green technologies is a key component in achieving these goals. This is reflected, inter alia, in the EU Eco-Innovation Action Plan (European Commission, 2011b), putting environmental technologies at the heart of environmental policy in the EU. Thus, the EU is specifically targeting the deployment of green technologies.

Despite the fact that governments are invested in encouraging innovative environmental technologies, there is little empirical evidence about whether or not these technologies have a positive environmental impact (Barbieri et al., 2016). One of the obstacles confronting researchers is the lack of a common mechanism to determine the effects innovation exerts on the environment (Barbieri et al., 2016). Still, it seems evident that if innovation is intended to lessen environmental damage, then the political pursuit of innovation can be justified. Several papers have shown that green technologies reduce environmental pressure (Carrión-Flores and Innes, 2010; Wang et al., 2012; Zhang et al., 2017), or at least positively affect environmental productivity (Costantini et al., 2017; Ghisetti and Quatraro, 2017; Weina et al., 2016).[59] However, findings remain ambiguous and unclear. Weina et al. (2016) come to the conclusion that green technologies contribute to improvements in environmental productivity, yet do not play a significant role in reducing the absolute emission level. All of these papers focus on the sectoral (Carrión-Flores and Innes, 2010), sectoral-regional (Ghisetti and Quatraro, 2017), sectoral-national (Costantini et al., 2017), or the regional level (Wang et al., 2012; Weina et al., 2016; Zhang et al., 2017), and employ emission indicators (mainly CO_2) to proxy environmental pressure.

When considering global environmental performance, every nation's efforts are important. If the governments of specific nations are responsible for reducing environmental pressure by committing to, e.g., the Paris Climate Agreement, determining whether or not environmental innovation is effective is of key importance. Hence, in this paper we will focus on European Union countries to provide insights concerning the impact of environmental innovation on environmental pressure at the national level. European Union countries are industrialized and share institutional commonalities, not the least of which is a strong commitment to pursue environmental innovation.[60]

As noted above, most studies on the effects of environmental innovations made use of emission indicators to operationalize environmental pressure. Yet it can be argued that such environmental indicators fail to capture the holistic nature of environmental pressure, including pressures at different stages of the economic process, as well as at different points in time (Agnolucci et al., 2017). Some scholars have proposed indicators such as those from Material

[59] Positively affecting environmental productivity refers to reductions in environmental damage per unit of output.
[60] The terms environmental innovation, green innovation and eco-innovation are not distinguished throughout this paper.

Flow Accounting as an alternative proxy of environmental pressure (among others, Fischer-Kowalski et al., 2011). The issues of environmental impact stemming from economic activity could relate to impacts on substance flows or soil erosion (Rockström et al., 2009). Some of these impacts may not be gone despite the treatment of particular pollutants. Material flow indicators are used, for example, as key indicators in the assessment of Sustainable Development Goals,[61] given that these indicators refer to various traits and qualify as a comprehensive measure of environmental pressure.

First, materials are resources that are inputs in the production function (O'Mahony and Timmer, 2009), and have both economic and environmental relevance. Not being perfectly recyclable, material usage reflects an irreversible depletion of environmental assets by humans. Second, materials capture potential environmental pressure at different stages. For example, the same material flow that causes land degradation at extraction may be the cause of harmful emissions at a later point in the value chain (e.g., the burning of fossil fuels). When viewed in this way, material inputs may be interpreted as waste potential that will, sooner or later, contribute to all sorts of environmental pressures (Weisz et al., 2006). It is for these reasons that the reduction of material use has become a central policy objective from the national to the global level (European Commission, 2011a, 2010, 2008; G7, 2015; OECD, 2016; United Nations, 2015).

This paper mainly contributes to two strands of literature. First, it will provide additional insights into the environmental effects of environmental innovation by widening the scope of this research strand. Comprehensive environmental indicators will be employed and a cross-country panel analysis will be conducted. Second, the paper will add to the literature on the determinants of material flows and decoupling (among others, Agnolucci et al., 2017; Krausmann et al., 2009; Shao et al., 2017; Steinberger et al., 2010; Weisz et al., 2006) by explicitly analyzing the impact of environmental innovation on national material usage.

Given that at the national level successful decoupling may be biased due to trade and outsourcing (Schaffartzik et al., 2016; Wiedmann et al., 2015), we will employ two material indicators in this paper. First, the well-established Direct Material Input (DMI) (Canas et al., 2003) indicator captures all materials entering the socio-economic system. Second, the Raw Material Input (RMI) indicator is calculated using global multiregional input-output (MRIO) models to account for upstream flows of foreign resource extraction related to imported commodities (Wiedmann et al., 2015).

[61] Material flow indicators are mentioned for Goal 12, see https://sustainabledevelopment.un.org/sdg12 [accessed August 09, 2019].

The results of our paper provide evidence that environmental innovation does reduce material usage at the national level. Neither general innovation nor overall environmental innovation is found to significantly affect material usage. Rather, specific areas of green technologies are associated with reductions in material usage, namely: recycling and reuse, and energy efficiency. We further find that GDP plays an important role in determining material usage. Our findings suggest that GDP affects RMI more strongly than DMI.

Section 2 offers a brief review of the literature dealing with the effects of environmental innovation and the determinants and decoupling of material flows. Section 3 develops the theoretical framework and hypotheses for our analysis. Section 4 introduces and describes the data. Section 5 explains the econometric model employed. Section 6 presents the empirical results and discusses the results concerning the effects of environmental innovation and decoupling. In section 7 several conclusions are drawn.

4.2 Literature Review

This paper draws upon the literature that deals with the environmental effects of environmental innovation, as well as the literature about decoupling and determinants of material flows.

If environmental innovation (EI) creates more efficient and less wasteful processing of materials, it is clearly related to material flows.[62] Generating energy from wind or solar power should reduce our reliance on fossil fuels. A more efficient product design can reduce the amount of raw materials and energy needed for production. More efficient vehicles reduce fuel consumption while providing the same level of mobility. These examples show how environmental innovation can reduce material usage without a concomitant decline in economic activity.

While there is some evidence that EI has a positive impact on environmental pressures, some confusion remains (Barbieri et al., 2016). Carrión-Flores and Innes (2010) find that EI reduced emissions for US manufacturing industries between 1989 and 2004, and that more stringent pollution targets induce innovation by increasing the cost savings of EI. Ghisetti and Quatraro (2017) find for sectors in Italian regions that EI increases the value added obtained per unit of emissions. Similar results are obtained for the impact of EI on sectoral performance in European countries, with EI improving the environmental performance both via a direct and an indirect

[62] The Community Innovation Survey 2008 questionnaire makes explicit enquiries as to the material-saving character of environmental innovations.

effect (Costantini et al., 2017). Furthermore, for industrial sectors in OECD countries, EI has led to reductions in energy intensity (Wurlod and Noailly, 2016). However, the evidence in studies examining the regional level remains rather inconclusive. Zhang et al. (2017) find for Chinese provinces that EI measures reduce CO_2 per capita. Focusing on total emissions in Chinese provinces, Wang et al. (2012) find no effect for innovation in fossil-fueled technologies, whereas innovation in carbon-free energy technologies is found significant for specific areas. In a study on 95 Italian regions between 1990 and 2010, Weina et al. (2016) conclude that for absolute environmental impact EI does not play a significant role, yet contributes to improved environmental performance.

A significant body of literature has emerged on the determinants of material flows (e.g. Haberl et al., 2006; Hoffrén et al., 2000; Pothen and Schymura, 2015; Schaffartzik et al., 2014; Weinzettel and Kovanda, 2011). This literature focuses on the influence of a wide variety of aspects, such as: economic growth (e.g. Agnolucci et al., 2017; Krausmann et al., 2009), population (e.g. Krausmann et al., 2009; Steinberger et al., 2010), affluence (e.g. Shao et al., 2017), changes in lifestyle (e.g. Steger and Bleischwitz, 2011; Voet et al., 2005), internationalization[63] (Steger and Bleischwitz, 2011), country specific factors (e.g. Steinberger et al., 2010; Weisz et al., 2006), and both the sectoral and the energy supply structure (e.g. Weisz et al., 2006).

A fundamental focus concerns dematerialization (Bithas and Kalimeris, 2017; De Bruyn, 2002; Krausmann et al., 2011; Shao et al., 2017; Steinberger et al., 2013). Dematerialization refers to relative or absolute decoupling of material use from economic growth (UNEP, 2011). Relative decoupling refers to decreases in material intensity without absolute reductions in resource use, and seems rather common (UNEP, 2011). Absolute decoupling (i.e., decreasing resource use in absolute terms) is much more rare (De Bruyn, 2002; Krausmann et al., 2011), being somewhat bound to phases of economic recessions (Shao et al., 2017). While the scale of the economy measured by GDP growth, should drive the environmental impact upward (Stern, 2004), three factors may cause material usage to lag behind increases in economic activity. Structural change, such as shifting from an industrial structure towards a service oriented economy, could cause a decrease in material intensity (Bithas and Kalimeris, 2017; Stern, 2004), although doubts as to this effect have been formulated (Kander, 2005; Steger and Bleischwitz, 2011). Furthermore, changes in the input structure (Stern, 2004), e.g., substitutions among materials

[63] Referring here to increased trade and embeddedness in the world economy, causing an increase in competitive pressure.

(Bithas and Kalimeris, 2017), could lead to reductions. Lastly, technological progress is considered to drive decreasing material intensity (Bithas and Kalimeris, 2017; Stern, 2004) either by a general increase in productivity and/or specific changes to reduce negative environmental consequences (Stern, 2004). Recent analyses corroborate caveats concerning the achievements of decoupling (Agnolucci et al., 2017; Bithas and Kalimeris, 2017; Schaffartzik et al., 2016; Wiedmann et al., 2015) that have also been raised at a more conceptual level (Ayres and Warr, 2004; Daly, 1987).

Although the effect of technological progress is a key component in determining material flows and achieving decoupling (Section 3), to the best of our knowledge there is no contribution in the literature explicitly analyzing the impact of environmental innovation on material flows. Given the high relevance of EI, its effects and associated technological change should be better understood to further the debate about technological change and decoupling.

4.3 Theoretical Framework and Hypotheses

We mainly draw upon three papers to gain a framework for this analysis (Steger and Bleischwitz, 2011; Steinberger et al., 2010; Voet et al., 2005). These papers are based on different theoretical foundations to identify the relevant determinants of material flows, yet converge on similar fundamental aspects. A common framework for the analysis of environmental pressure is the IPAT hypothesis (Dong et al., 2017; Steinberger et al., 2010; Weina et al., 2016). It states that environmental impact results from population size and affluence,[64] and the technologies used. As materials per unit of GDP could be a proxy for technology (Dong et al., 2017), compliance with the intensity of use hypothesis (Malenbaum, 1978) is obvious.[65] This hypothesis states that materials are a function of the countries' income multiplied by the prevailing material intensity (Voet et al., 2005).[66] Thus, these hypotheses can be grouped into three relevant effects: a growth effect influencing the scale of economic activity, a compositional effect influencing material intensity, and a technology effect influencing material intensity (Voet et al., 2005).

[64] GDP per capita (Dong et al., 2017).

[65] The application of the hypothesis to this context would be:
IPAT: Materials = Pop * GDP/Pop * Materials/GDP = GDP*Materials/GDP
IoU: Materials = GDP* Materials/GDP

[66] Materials per unit of income.

Defining these pillars aligns with factors considered as relevant drivers of environmental impact and material intensity mentioned in the discussion on decoupling. Stern (2004) considers proximate variables for environmental impact to be the scale of production, structural change, changes in the input mix, and technological progress. Bithas and Kalimeris (2016) consider structural change, technological progress, and substitution among materials to qualify as relevant factors for material intensity.

Based on these considerations, we group our determinants into four pillars, from which we derive our main variables. The first aspect could be referred to as a scale or growth effect. This can be considered an overall growth effect as reflected in overall GDP growth (Voet et al., 2005). The second pillar could be referred to as structural change (e.g., transitioning from an industrial base to a more services oriented economic structure), influencing the composition of production and consumption (Voet et al., 2005). Our third pillar is technological progress, as it influences the effect of economic activity on material flows (Dong et al., 2017; Hoffrén et al., 2000; Steger and Bleischwitz, 2011; Voet et al., 2005). Lastly, there should be a pillar for factors that affect the material usage of countries without being subject to the aspects mentioned above. Among these factors are aspects such as the climate (Steinberger et al., 2010; Voet et al., 2005; Weisz et al., 2006) or land area (Steinberger et al., 2010; Weisz et al., 2006), which are country-specific and rather constant, complemented by institutional (Steger and Bleischwitz, 2011), cultural, or other infrastructural specificities.

To include the first three pillars in our analysis we will now define three key variables. Due to the econometric model employed (Section 5) variables of the last pillar, which are constant within a country, need not be taken into account. Our main variable of interest is the impact of green technological change, captured by the green knowledge stock. Technological change should contribute to reducing material usage (Dong et al., 2017; Steger and Bleischwitz, 2011; Voet et al., 2005). This is especially expected for our measures of green innovation. To capture the scale effect of the economy, we use GDP. Ceteris paribus, growth should lead to a proportional increase in environmental damage (Voet et al., 2005). Structural change in production is captured by the share of the industry sector in the value added of a country.[67] The industry sector is assumed to be more material-intensive (Weisz et al., 2006), contributing to higher levels of material usage.

[67] The industry sector is defined on the 3-sector-data level in the Cambridge Econometrics European Regional Database (ERD). The industry sector is aggregated from the 6-sector-data by combining manufacturing and energy, and construction.

4.4 Data

The dataset consists of a panel of EU-27 countries, spanning the period from 1990 to 2012. These countries are closely tied to each other both economically and politically due to the framework of the European Union. While sharing similar economic and institutional environments, they are politically pursuing environmental innovation as a means to reduce material usage (European Commission, 2011b, 2010). Especially within the EU-15, a shared history and homogeneous economic structures and surroundings may prevent distinctive patterns caused by path-dependency or specific developmental stages. It can also be assumed that the preparations required for membership of the twelve countries that joined the EU in 2004 and 2007, have caused some homogeneity as well. Croatia is not included in our dataset, as it joined after the end of our observation period.

The time period considered starts after the collapse of the Soviet Union. This time restriction is mainly caused by the data availability of our dependent variable, but may support homogeneity between countries and patterns. The Soviet Union's dismantling also marks a significant change in the global geopolitical landscape, as any number of countries were under pressure and pursued a transitional path towards market economies.

The material usage of an economy is measured by capturing its material input.[68] This reflects the material requirements of the economy for consumption and production (see Bringezu et al., 2004). The indicator is derived from the methodology of Material Flow Accounting and encompasses all materials that enter the socio-economic system of a country (Fischer-Kowalski et al., 2011). It proxies resource inputs (Bringezu et al., 2004) and is comprised of a country's domestic extraction within a given year, plus the imports of materials. Similar indicators would be material consumption indicators, measured by subtracting exports from material input. From our perspective, consumption indicators are less suited to capture the material requirements of a country. For example, as a consequence of technological change, material inputs for the production of export goods could be reduced. Consumption indicators would fail to capture such an effect, as the materials used would not be captured in a country's material usage.[69]

[68] We construct the Total Material Input, which is equal to adding up the subcategories biomass, fossil fuels, metal ores, and non-metallic minerals (see also Agnolucci et al., 2017).
[69] For example, advances in technology may cause fewer material needs from imports as intermediate inputs. However, when the goods are exported as final products, the full quantity of embodied materials would be gone, thus losing information of this kind.

We construct two distinct indicators to capture material input, namely the Direct Material Input (DMI) and the Raw Material Input (RMI). DMI is one of the most commonly used indicators, and measures the mass of domestically extracted materials plus import flows (Canas et al., 2003). The difference between DMI and RMI is based on the calculation of imported materials. DMI calculates imported materials and goods at the border by their actual weight, whereas RMI calculates imports by their so-called Raw Material Equivalents (RME) (UNEP, 2016). RMEs include the upstream material requirements of imported commodities (UNEP, 2016). To calculate these requirements, a global multiregional input-output analysis is applied (Wiedmann et al., 2015).

There are both advantages and disadvantages in using RMI and DMI for our analysis. RMI has the advantage that upstream flows are incorporated. Hence, the issue of offshoring environmentally-intensive production steps is controlled (Schaffartzik et al., 2016), and distortions from the positioning of countries in global value chains are avoided. Furthermore, a successful reduction of inputs required for production would be associated with an even stronger decrease of material inputs, as upstream requirements are also reduced. On the flipside, RMI may be more sensitive to changes in foreign technology if changes in material usage are not due to domestic technology but to changes in the material usage generated upstream. Furthermore, the calculation of the data by means of an input-output analysis suffers from issues and uncertainties inherent in the application of input-output models (Eisenmenger et al., 2016). For DMI, the opposite considerations apply. One disadvantage is that upstream requirements are not included. This may obscure results if reductions are basically due to offshoring material intensive production processes in the course of trade activities (Wiedmann et al., 2015). Moreover, global material reduction is not fully accounted for when imports are effectively reduced. An advantage is that DMI directly reflects the mass of materials actually processed in the economic system, without potential issues due to foreign changes in technology and production, and uncertainties stemming from the application of input-output models.

The material flow data used was obtained from the United Nations Environment Programme (UNEP) material flow dataset (UNEP, 2016), available publicly for download at http://www.resourcepanel.org/global-material-flows-database. Because the time-series for Raw Material Equivalents is restricted to 1990 to 2012,[70] our two dependent variables are constructed for these years.[71] From the database we obtained data on the MF4 level, which separates

[70] Although later years are available, it is stated in the Technical Annex that data after 2012 should not be used for statistical analysis, as data is increasingly projection based.
[71] Though data on domestic extraction and regular imports would be available for earlier years.

materials into four categories: biomass, fossil fuels, metal ores, and non-metallic minerals. In this paper, we focus on the aggregated total of material input, meaning the summation of the values for the four subclasses (Agnolucci et al., 2017). Aggregating the data has the disadvantage of losing the ability to observe different effects on different subgroups. However, focusing on the aggregate material usage is in line with other works (Agnolucci et al., 2017) and a good starting point to identify aggregate dynamics. For each subgroup of materials we calculated the Direct Material Input by adding domestic extraction (DE) and imports (Im). For the Raw Material Input we added the RMEs of imports (RME_{IM}) to DE. If any of the two required subcategories (DE and Im/RME_{IM}) were missing, we set the DMI or RMI for that material class as missing. The aggregate indicator was then generated by adding up RMI and DMI of all material classes, and setting the aggregate indicator to missing if any of the subgroups were missing. Finally, we set RMI to missing if there was no data on regular imports. Thus, we have a harmonized availability of DMI and RMI for the same countries and years, facilitating a comparable analysis of both indicators.

To operationalize technological innovation, we rely upon patent counts, which are used to generate patent stocks as a measure of the installed and available technological capability (Costantini et al., 2017; Popp et al., 2011). Patents are generally considered to be a good indicator of innovative activity and are also strongly related to other measures of innovation (Griliches, 1990). However, some drawbacks have been extensively discussed in the literature. First, a major issue can be differing patent quality. This may result from different propensities to patent, different patent regimes requiring different amounts of patents for the same invention, and different economic values of an invention (Johnstone et al., 2010; Popp et al., 2011). Second, although few economically significant inventions have not been patented (Dernis and Khan, 2004), there are some inventions that may not be patented (Haščič and Migotto, 2015). Thirdly, when searching for specific environmental patents two possible errors may arise: either the inclusion of irrelevant patents, or the exclusion of relevant patents (Lanjouw and Mody, 1996).[72]

In spite of these issues, there are certain advantages of using patent data for our analysis. Next to measuring intermediate output and being widely available, patent data are quantitative and can be disaggregated by technological classes (Haščič and Migotto, 2015). Disaggregated technology classes allow us to formulate specific search strategies identifying specific

[72] These issues do not prevent conclusive arguments on parameters found to be significant, while an overestimation of green patents can increase the risk of not finding statistically significant coefficients, although the true parameter value would be significant (Wurlod and Noailly, 2016).

environmental technology domains. For these reasons, we rely on patent data for this study and formulate a search strategy to minimize the issues mentioned above.

We retrieve patent data using PATSTAT 2017b.[73] Given the alternatives in generating patent based measures, we decided to rely on multinational patent applications at the European Patent Office (EPO) to avoid issues of patent value and comparability. Only innovations of high value with expected commercial profitability justify the relatively high application costs of an EPO patent (Johnstone et al., 2010). To avoid counting technologies multiple times and to enhance the value of included patent applications, we only take the first EPO patent application within a patent family. As we are interested in the economic utilization of an invention, we rely on applicant data to assign patents (Ghisetti and Quatraro, 2017) and count the number of patent applications in which an applicant from a country is involved. We use patent applications instead of granted patents, thus capturing the whole innovative effort (Costantini et al., 2017). Using the earliest filing year is considered preferable because it is a better reflection of the timing of the discovery. It is not influenced by regulatory delays (Carrión-Flores and Innes, 2010), and is common practice in similar empirical applications (Carrión-Flores and Innes, 2010; Costantini et al., 2017; Wang et al., 2012; Weina et al., 2016; Wurlod and Noailly, 2016).

We distinguish environmental and non-environmental innovation based on the technological classes of patent applications. We utilize search strategies provided by the World Intellectual Property Organization (WIPO) and the OECD. To capture environmental innovation we combine the established WIPO Green Inventory (GI) (Albino et al., 2014; Ghisetti and Quatraro, 2017; Kruse and Wetzel, 2014) with the latest version of the OECD EnvTech indicators (EnvTech) (Costantini et al., 2017; Ghisetti and Quatraro, 2017; Haščič and Migotto, 2015). The EnvTech now largely integrates the EPO Y02 scheme for climate-related technologies. Furthermore, we define search strategies identifying specific technological areas, given that some technological domains within these classifications do not relate to changes in material usage.

We construct the category overall environmental innovation (EI_Full), by including all technological classes mentioned in the GI and/or the EnvTech[74] to capture all green innovations. We also distinguish five specific EI domains that we believe have the ability to capture specific effects on material usage. We utilize subsets of the above-mentioned classifications to construct

[73] The b refers to the autumn version.

[74] The Green Inventory can be found at: https://www.wipo.int/classifications/ipc/en/green_inventory/ [accessed August 09, 2019]

The OECD Env Tech can be found at: https://www.oecd.org/environment/consumption-innovation/ENV-tech%20search%20strategies,%20version%20for%20OECDstat%20(2016).pdf [accessedAugust 09, 2019] the following EI domains: alternative energy production (EI_AEP), transportation (EI_Transp), recycling and reuse (EI_Recy), energy efficiency (EI_EnEff), and climate change mitigation in the production or processing of goods (EI_ProGo). Table 1 gives an overview of the technology areas used for the construction of these domains. A comprehensive list of the included technological classes of each domain classification can be found in the Appendix (A4). A variable of general innovation was constructed including all patents (Total Inno). Non-green counterparts of our EI domains are constructed based on those patents that do not belong to any technological class included in the corresponding EI domain.[75]

Table 1: Overview of the construction of Environmental Innovation (EI) Domains

EI_AEP **Green Inventory Areas** Alternative Energy Production **OECD EnvTech Areas** 4.1. Renewable Energy Generation 4.2. Energy generation from fuels of non-fossil origin 4.3. Combustion technologies with mitigation potential
EI_Transp **Green Inventory Areas** Transportation **OECD EnvTech Areas** 6. Climate change mitigation technologies related to Transportation

Table 1 continues

[75] As an illustration, NG_Recy includes all patents that do not belong to any IPC/CPC class that is mentioned in the EI_Recy technology classes list.

EI_ProGo **OECD EnvTech Areas** 9. Climate change mitigation technologies in the production or processing of goods
EI_Recy **Green Inventory Areas** Reuse of waste materials (subarea of Waste Management) **OECD EnvTech Areas** 1.3.2. Material recovery, recycling and re-use 1.3.3. Fertilizers from waste 4.2.2. Fuel from waste 8.2.5. Reuse, recycling or recovery technologies 9.6.5. Technologies for production of paper and paper articles **OECD EnvTech Classes from** 1.3.4. Incineration and energy recovery 8.3. Enabling technologies or technologies with a potential or indirect contribution to GHG emissions mitigation 9.1.2. Process efficiency 9.2.1. General improvement of production processes causing GHG emissions 9.2.5. Improvements relating to the production of other chemicals or pharmaceuticals 9.5.8. Food processing 9.6.2. Technologies for metal working 9.6.6. Technologies for working on or processing of plastics 9.6.13. Technologies for production or treatment of textiles and foot wear 9.7. Climate Change Mitigation Technologies for sector-wide applications
EI_EnEff **Green Inventory Areas** Energy conservation **OECD EnvTech Areas** 4.5. Technologies for an efficient electrical power generation, transmission or distribution 4.6. Enabling technologies 4.7. Other energy conversion or management systems reducing GHG emissions 7.2. Energy efficiency in buildings 7.3. Architectural or constructional elements improving the thermal performance of buildings 7.4. Enabling technologies in buildings 9.6.5. Technologies for production of paper and paper articles **OECD EnvTech Classes from** 9.1.2. Process efficiency 9.2.1. General improvements of production processes causing GHG emissions 9.4.1. Production of cement 9.5.1. Agricultural machinery or equipment 9.6.1. Technologies for shaping products 9.6.2. Technologies for metal working 9.6.6. Technologies for working on or processing of plastics 9.6.13. Technologies for production or treatment of textiles and foot wear 9.7. Climate Change mitigation technologies for sector-wide applications

Notes to Table 1: *"(Green Inventory/ OECD EnvTech) Areas" refers to sections of which all technological classes were included for the EI domain. "(Green Inventory/ OECD EnvTech) Classes from" refers to sections of which only specific technological classes were included. A detailed overview of the technology classes constituting each EI domain is provided in the Appendix (A4).*

Following previous work (Costantini et al., 2017; Popp et al., 2011; Weina et al., 2016; Wurlod and Noailly, 2016), we construct patent stocks based on the patent count data we have obtained.[76] Thus, we generate a measure of the installed technological capability (Costantini et al., 2017). We follow Popp et al. (2011) in constructing a knowledge stock that accounts for both the diffusion of new technologies and the declining influence of older technologies. Hereby, we account for the fact that the effect of new technologies may not be instantaneous and that older technologies' effects should decrease over time (Weina et al., 2016). The generation of the patent stock for country i in year t follows the formula (Popp et al., 2011):

$$(1)\ K_{i,t} = \sum_{s=0}^{\infty} e^{-ß_1(s)}\left(1 - e^{-ß_2(s+1)}\right)PAT_{i,t-s}$$

By multiplying the rate of diffusion with s+1, diffusion is not constrained to zero in the current period (Popp et al., 2011). The rate of knowledge depreciation is set to 0.1 ($ß_1$) and the rate of diffusion to 0.25 ($ß_2$) (Popp et al., 2011; Weina et al., 2016).

Data on additional variables was taken from various sources. Data on Gross Domestic Product (GDP), the sectoral value added,[77] and population was retrieved from the Cambridge Econometrics European Regional Database (ERD). Data on the share of renewables in Total Primary Energy Supply (TPES) was taken from the OECD. The data on the share of the urban population as well as trade data was taken from the World Bank. The data on the share of imports and exports in relation to GDP were retrieved and summed up to generate the variable trade openness. A list of descriptive statistics can be found in the Appendix in Table A1. The stationarity of the variables was tested using unit root tests. Relying on the Fisher-Test with drift, the share of renewables in TPES is non-stationary in levels (Appendix, Table A2).

4.4.1 Material Inputs

We now explore in detail our chosen dependent variables of Raw Material Input (RMI) and Direct Material Input (DMI). First, we will discuss differences between the two indicators in magnitude and then their different dynamics over time. For RMI, the smallest value can be found for Malta in 1990 with 7.4 million tons (MT), while the largest value is found for Germany in 2008 with ~2,377 MT. For DMI, the largest value is found again for Germany with ~1,495 MT in 2007. The lowest value for this indicator is found for Malta in 1995 with 5.2 MT.

[76] We initially construct our stocks starting with count data from 1980 onwards.
[77] Sectoral value added was used to calculate the share of the industry sector.

These proportions between the two indicators also hold across the entire sample, as on average RMI is 1.5 times as high as DMI. Yet, this RMI/DMI ratio is variable across the sample, ranging from 0.88 to 3.28.[78] The strongest divergence between the two indicators occurs in Malta in 1991 with RMI being 3.28 times as high as DMI. Only few cases occur in which DMI is larger than RMI, namely in Bulgaria (1996 and 1997), the Netherlands (1990), Poland (1990), and Romania (1990 and 1991). The highest average deviations of the two indicators (RMI/DMI ratio) are found for Luxembourg (2.28), Slovakia (1.94), the United Kingdom (1.89), Lithuania (1.74), and Italy (1.71). The lowest average differences are found for Bulgaria (1.09), Belgium and Estonia (1.16), Romania (1.20), and the Netherlands (1.21). Some countries show a large variation in this ratio, such as Luxembourg (Min.: 1.37 ; Max.: 2.99), Malta (Min.: 1.26 ; Max.: 3.28), Slovakia (Min.: 1.43 ; Max.:2.59), and the United Kingdom (Min.: 1.34 ; Max.: 2.37). Other countries show very little variation, for example Bulgaria (Min.: 0.96 ; Max.: 1.14), Estonia (Min.: 1.08 ; Max.: 1.24), and Sweden (Min.: 1.30 ; Max.: 1.48).

The share of materials extracted domestically, the so-called domestic resource dependency (DRD) (Weisz et al., 2006), plays an important role as the import of materials may hide upstream flows (Eisenmenger et al., 2016; Schaffartzik et al., 2016). In line with the observations on the RMI/DMI proportions, the DRD is higher in the case of DMI (~70%) than it is for RMI (~49%). This indicates that DMI does not value equally the fact that most imports are associated with upstream flows. These are accounted for in RMI, raise the mass of imports, and thus lower the share of domestic extraction. The DRD is expected to diminish when a country is placed further downstream in the value chain, meaning that more suppliers are upstream before materials are refined in the country. In our sample the highest average levels of DRD (>80% in DMI and >70% in RMI) are found for Bulgaria, Estonia, Poland, and Romania.

Additional insights into the dependent variables are acquired when analyzing their dynamics over time. First, we look at the difference between the first and the last observed value for RMI and DMI in each country. For all countries the relative increase of RMI is larger than DMI’s, although quite small in some countries (e.g., in Bulgaria RMI grew 10 percentage points more than DMI), while very large in others (e.g., in Luxembourg RMI grew 155 percentage points more than DMI). Also, the final RMI values are larger than the initial ones across all countries, while DMI shows smaller values at the end of our time-period in several countries: United

[78] 0.88 indicates that RMI amounts only to 88 if DMI is set at 100, while 3.28 indicates that RMI is 328 if DMI equals 100.

Kingdom -26%, Hungary -23%, Romania -22%, Italy -5%, Greece -3%, and the Czech Republic -1%.

These findings correspond to the different growth dynamics of RMI and DMI. RMI grows on average at a rate of almost 3%, while DMI only about 1.4%. Across all countries average RMI growth is larger than DMI growth, with all countries having a positive RMI growth rate. The only country with less than one percent average RMI growth is Hungary (0.82%), while Cyprus, Estonia, Luxembourg, Latvia, and Malta have more than 5% growth on average. Concerning DMI, Hungary, Italy, Romania, and the United Kingdom have negative average growth rates. Hence, the two indicators do not only lead to differences in magnitude, but also represent different dynamics over time. The higher growth rate of RMI indicates an increasing importance of offshoring material-intensive production processes.

4.4.2 Knowledge Stocks

For each of our distinct patent search strategies we construct a knowledge stock based on Formula 1. In Table 2, we report the top 5 countries for our six environmental innovation variables and the general innovation variable, as well as the descriptive statistics. The top countries are Germany, France, Italy, Netherlands, and the United Kingdom (UK). This largely corresponds to the level of economic development, and the size of the countries. These countries, ranked by their mean value, always take the first five places. The only exception concerns transportation, where the Netherlands is ranked 7 behind Austria and Sweden.

Table 2: Countries with largest average knowledge stock by innovation type

Innovation type	Country	Mean	Std. Dev.	Min	Max
Total Inno	Germany	99961.1	41160.3	40818.4	167442.2
	France	36193.9	12907.2	16460.3	58069.8
	UK	24311.1	6462.8	13416.4	33762.0
	Netherlands	18029.6	7661.0	7213.5	29821.7
	Italy	16432.5	6860.4	6160.4	27096.8

Table 2 continues

EI_Full	Germany	17976.7	7751.8	7269.7	32174.1
	France	5871.5	2025.6	2823.1	9765.6
	UK	4213.5	1258.4	2138.2	6069.0
	Netherlands	2859.4	1265.6	1155.9	5103.5
	Italy	2129.1	990.1	795.5	3912.4
EI_EnEff	Germany	3372.3	1822.5	1157.0	7326.6
	France	1105.8	414.1	536.0	2079.5
	Netherlands	881.5	533.8	254.1	1871.9
	UK	730.0	237.1	396.9	1195.8
	Italy	438.0	254.0	107.4	915.1
EI_AEP	Germany	5955.6	2312.3	2872.2	10342.2
	France	2044.4	647.6	1041.3	3194.4
	UK	1767.4	572.3	831.0	2441.0
	Netherlands	1164.9	413.0	578.9	1908.5
	Italy	692.0	292.4	328.6	1275.9
EI_ProGo	Germany	1346.2	648.4	518.7	2658.4
	France	444.6	167.7	200.8	798.9
	UK	295.1	91.8	170.4	482.9
	Netherlands	221.6	106.0	90.4	460.4
	Italy	206.9	91.3	71.6	366.7
EI_Transp	Germany	2662.7	1590.8	738.6	6008.2
	France	981.2	496.8	389.1	2072.7
	UK	414.1	138.2	222.2	726.4
	Italy	341.3	153.0	135.2	623.7
	Austria	207.0	93.5	72.4	409.1
EI_Recy	Germany	957.2	244.2	415.7	1309.3
	France	295.5	67.3	160.3	425.4
	UK	197.7	58.0	93.1	279.7
	Italy	156.5	65.7	56.4	266.4
	Netherlands	154.5	52.2	62.1	247.5

Germany and France hold the top 2 spots in every category, although Germany has by far the largest knowledge stock in our sample with values that are almost three times as high as France. Generally, the UK follows in third place followed by the Netherlands and Italy. In the case of energy efficiency (EI_EnEff), the Netherlands shows higher values than the UK. When it comes to recycling and reuse (EI_Recy), Italy shows slightly higher values than the Netherlands, and in the case of transport (EI_Transp) the Netherlands drops out of the Top 5 being replaced by Austria. All countries involved are EU-15 countries with a larger population and a high level of economic development.

As Figure 1 shows, knowledge stocks tend to increase over time. For the average EU-27 country, the knowledge stock increases in all EI domains. Norming all values to 1 in 2001 shows that all EI domains start at ~0.5 in 1990 and develop upwards to 1 in 2001. After 2001, transportation (EI_Transp) and energy efficiency (EI_EnEff) show the largest increase reaching ~2.4 in 2012. Production or processing of goods (EI_ProGo) also reaches a value above 2 in 2012, while overall environmental innovation (EI_Full) and alternative energy production (

EI_AEP) reach ~1.8 of their 2001 value. The smallest increase can be found for recycling and reuse (EI_Recy) remaining below 1.5 in 2012.

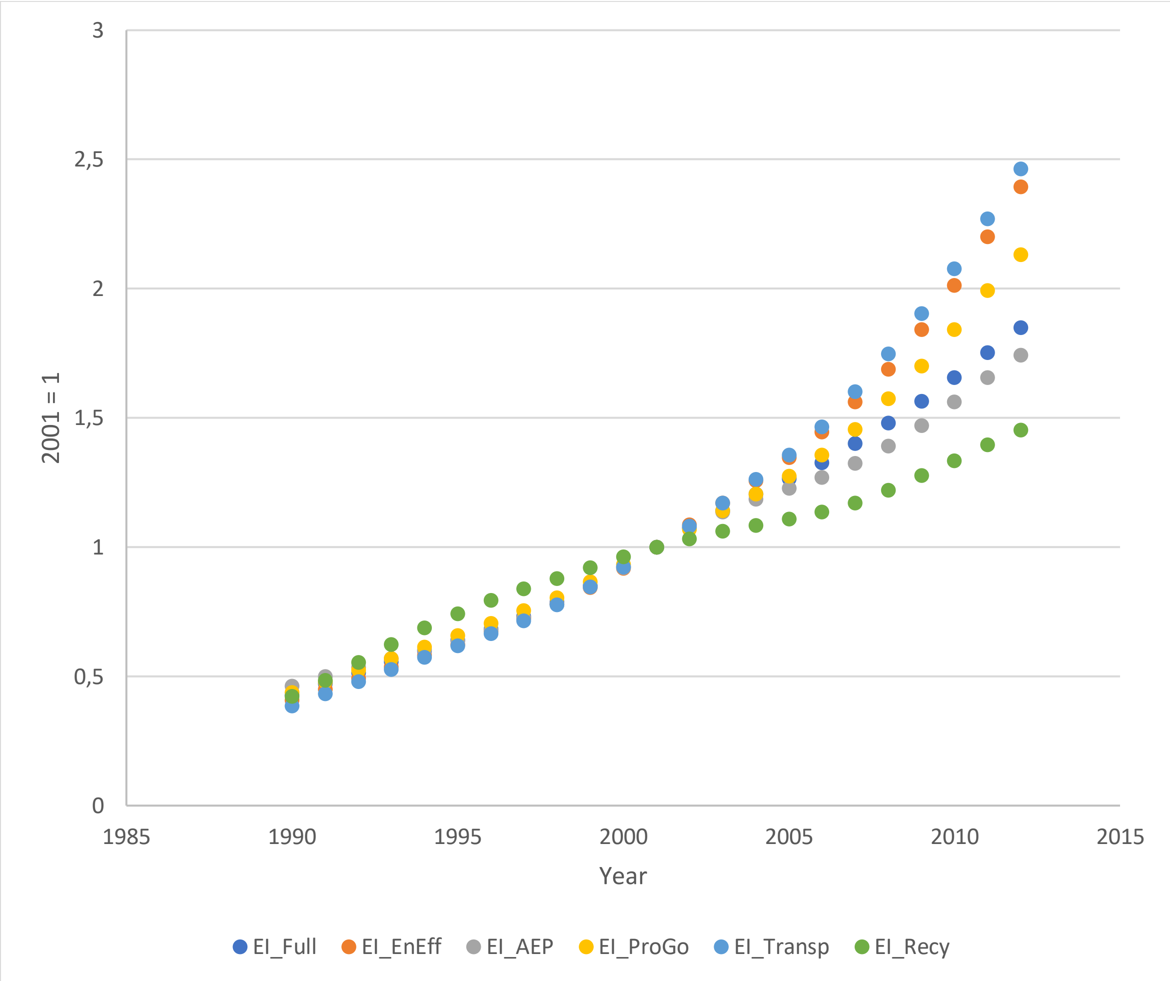

Figure 1: Development of the average EU-27 patent stock between 1990 and 2012 by EI domain. *All variables were normed by their value in 2001.*

In terms of absolute numbers, EI_Recy is the smallest category, followed by EI_ProGo and EI_Transp. EI_AEP is by far the largest EI domain, with an average value roughly 1.8 times as high as EI_EnEff. Descriptive statistics on the knowledge stock variables can be found in the Appendix (Table A1).

4.5 Econometric Model

In view of the literature on panel data and our research question, a dynamic approach should be adopted to account for the dependency of material flows on their own past values (see Shao et al., 2017). We will formulate equivalent equations for DMI and RMI. The model to be estimated is given by:

$$(2)\ DMI_{it} = \sum_{j=1}^{J} \gamma_j DMI_{it-j} + X'_{it}\beta + \varphi_i + \epsilon_{it}$$

with the subscript i= 1,…,N denoting the countries, and t = 1,…,T the years of the panel. The vector X includes the explanatory variables, β denotes the vector of coefficients. φ is the country fixed effect, and ϵ is the error term.

Estimating a fixed-effects model with a lagged dependent variable (LDV) as a regressor generates a biased estimate of the coefficients (Judson and Owen, 1999). If the time dimension becomes sufficiently large, the correlation between the LDV and the country-specific effect might be small (Castro, 2013). Even for T=30 the bias can amount to 20% of the true value of the coefficient (Judson and Owen, 1999). As in our application we are dealing with T=~20, this bias should be seen as potentially strong. This suggests that a one-step difference Generalized Method of Moments (GMM) estimator, as proposed by Arellano and Bond (1991), should be used (Hwang and Sun, 2018; Judson and Owen, 1999).

The starting point of this estimator is given by first differencing the equation:

$$(3)\ \Delta DMI_{it} = \sum_{j=1}^{J} \gamma_j\ \Delta DMI_{it-j} + \Delta X'_{it}\beta + \Delta\epsilon_{it}$$

Thus, the country-specific effects are eliminated and instrumental variable estimators can be used. These estimators allow the inclusion of endogenous regressors, as well as predetermined and exogenous regressors. Endogenous regressors are influenced by the contemporaneous error term, while predetermined regressors may be influenced by the error term in previous periods. The differentiation process has the disadvantage that while the fixed effects are gone, Δy_{t-1} is now correlated with $\Delta\epsilon_{it}$ as y_{t-1} is a function of ϵ_{it-1}.

This problem can be solved by instrumental variables. Lags of the dependent variable and the regressors can be used to satisfy the moment conditions:

$$(4)\ \ E[DMI_{it-s}\Delta\epsilon_{it}] = 0\ \ and\ \ E[X_{it-s}\Delta\epsilon_{it}] = 0$$

$$for\ t = j+2, \dots, T\ and\ s\ \geq j+1$$

The orthogonality restrictions above are the basis of the one-step GMM estimation. While exogenous regressors instrument themselves in first differences, predetermined and endogenous variables are instrumented with their lagged levels. For predetermined variables lags 1 and deeper are available, for endogenous variables lags 2 and deeper.[79] Instrumenting with lagged levels instead of lagged differences makes one time period more available.[80]

The procedure requires that no second-order autocorrelation is present in the differenced equation. First-order correlation is expected in differences as the $\Delta\epsilon_t$ and $\Delta\epsilon_{t-1}$share a common ϵ_{t-1} term, thus evidence is uninformative. Autocorrelation of a higher order than one in the differenced equation would render some instruments invalid and would require deeper lags to be used as instruments, causing a loss of T (Roodman, 2009). The presence of second-order autocorrelation would generate inconsistent estimates (Castro, 2013).

Crucial for the validity of GMM is exogeneity of the instruments. When the number of regressors k is equivalent to the number of instruments j, the model is exactly identified and the detection of invalid instruments becomes impossible. Yet, if the model is overidentified with j > k, validity of the instruments can be tested using the Sargan specification test (Castro, 2013; Roodman, 2009).

Special attention, especially in a larger T context, should be given to restricting the number of instruments used, as too many instruments impose problems for GMM estimation (Roodman, 2009). This consideration motivates the sparse use of instruments to avoid instrument proliferation, as is carried out in the empirical application and explained in section 6. We will check the results for reductions in the instrument count.

4.6 Empirical Results and Discussion

We begin the empirical analysis by specifying and validating a baseline model using our three main explanatory variables and the lagged dependent variable (LDV). Then we turn to the estimation for our two dependent variables with the various classifications of green technological areas. To ensure that we identify an actual effect and avoid issues of omitted variable bias in our innovation variable, we also check for the effects of total innovation and the non-green counterparts of the green technological areas that were previously found to exert a significant effect on material usage. We further explore several variables that may be

[79] A predetermined variable X_t is influenced by past error terms, e.g. ϵ_{t-1}. Thus, in first-differences X_{t-1} is a valid instrument for ΔX_t as it is only correlated with ϵ_{t-2}, and thus not with $\Delta\epsilon_t$.
An endogeneous variable is correlated with the contemporaneous error term. Thus, to instrument ΔX_t one would need X_{t-2} as X_{t-1}would be correlated with the ϵ_{t-1} in $\Delta\epsilon_t$.

[80] A first-difference instrument would be available for the first time in the fourth period, while a lagged level instrument is first available in the third period.

considered to affect material usage and check them for inclusion in our model. Lastly, we check the robustness of our results for reductions in the instrument count.

4.6.1 Main Results

In our estimations, the variables in all specifications are either in natural logarithm or share. In line with the respective tests and literature (Roodman, 2009), all specifications include time-effects. Concerning the fixed-effects estimation, the Hausman test supports estimating a fixed-effects instead of a random-effects model. The regular fixed-effects model is estimated with Driscoll and Kraay standard errors (FE DK), that are robust to cross-sectional dependence, heteroscedasticity, and autocorrelation (Hoechle, 2007). We use the FE estimator to initially ensure the soundness of the Arellano-Bond estimation concerning the coefficient of the LDV. We report the coefficients and in brackets the robust standard errors. As to the tests, we report the respective statistic and the p-value in brackets.

To overcome bias and inconsistency in OLS estimation methods, we employ the Arellano-Bond estimator. The difference one-step GMM estimator was used, in line with econometric literature (Hwang and Sun, 2018; Judson and Owen, 1999) and similar applications (Castro, 2013; Wang et al., 2012). In our baseline model we include one lag of the dependent variable to allow past material use levels to influence current material use (Shao et al., 2017), the stock of green knowledge (Costantini et al., 2017), GDP, and the industrial intensity as explanatory variables. In the Arellano-Bond estimation (AB), the LDV is instrumented with the second to tenth lag of the non-lagged dependent variable. Environmental innovation is treated as potentially endogenous (Costantini et al., 2017) and instrumented with the third to fifth lag. GDP is treated as endogenous and instrumented with its second and third lag. The industrial intensity is treated as exogenous. Concerning the LDV, the use of more lags as instruments presents a trade-off as a large instrument count may weaken the reliability of our results (Roodman, 2009), given that we have 27 cross-sectional units in our sample. However, we check the robustness of results to different instrument choices. The robustness of our results in relation to the reduction of the instruments is shown in the Appendix (Table A3e). Furthermore, all AB estimations are conducted with orthogonal deviations instead of a first-difference transformation (Hayakawa, 2009; Hsiao and Zhou, 2017; Roodman, 2009). Especially, when the lag range is restricted, orthogonal deviations lead to asymptotically unbiased estimates (Hsiao and Zhou, 2017). The consistence of the estimator is assured as the AR tests for serial correlation in the differenced residuals provide no evidence of second-order autocorrelation. The validity of the employed instruments is confirmed by the results of the Sargan test.

We start by checking the soundness of the AB estimation by estimating our baseline model with OLS, FE, and AB (Table 3). To be sound, the coefficient of the LDV in the AB estimation should lie in or near the range of the coefficient size of OLS (upward biased) and FE (downward biased) (Roodman, 2009). This condition seems to hold, given the standard errors of the LDV. The results provide support that the AB specifications are sound, hence we will continue with AB estimation in further analysis.

Table 3: Results of OLS, Fixed-Effects and GMM for RMI and DMI

	(1)	(2)	(3)	(4)	(5)	(6)
Model	OLS	FE DK	AB	OLS	FE DK	AB
Dep. Var.	Raw Material Input	Raw Material Input	Raw Material Input	Direct Material Input	Direct Material Input	Direct Material Input
L1. Raw Material Input	0.958***	0.583***	0.378*			
	(0.0130)	(0.0970)	(0.193)			
L1. Direct Material Input				0.971***	0.768***	0.800***
				(0.00879)	(0.0512)	(0.0696)
EI_Full	-0.00620*	0.00700	-0.0105	-0.00380	0.00267	-0.0203
	(0.00341)	(0.00932)	(0.0335)	(0.00287)	(0.00837)	(0.0184)
GDP	0.0373**	0.285***	0.584***	0.0236**	0.158**	0.276*
	(0.0149)	(0.0631)	(0.202)	(0.00953)	(0.0639)	(0.141)
Industrial Intensity	0.120**	0.627**	0.602	0.111*	0.473**	0.316*
	(0.0562)	(0.252)	(0.407)	(0.0577)	(0.192)	(0.183)
Time-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	559	559	532	559	559	532
No. of Countries	27	27	27	27	27	27
R-squared	0.997	0.9045		0.998	0.8803	
No. of Instruments			36			36
AR1-Test			-2.25 [0.024]			-3.56 [0.000]
AR2-Test			0.86 [0.389]			-0.06 [0.955]
Sargan-Test			18.67 [0.067]			11.59 [0.395]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Our main variable of interest is environmental innovation (EI), proxied by a knowledge stock derived from data on environmental patent applications, as we are interested in its potential to contribute to reductions of material usage. We use a green knowledge stock accounting for the diffusion and depreciation of technologies (Popp et al., 2011). Utilizing a holistic definition of green innovation (EI_ Full), which includes all technologies of the Green Inventory (GI) and/or the OECD EnvTech (EnvTech), we do not find that EI affects material usage, neither when using the Raw Material Input (RMI) nor when using Direct Material Input (DMI).

We continue by briefly discussing the results concerning the other determinants of material usage included in our model before we continue analyzing our main variable of interest (EI) in more detail, focusing on specific technological areas. We include the first lag of the dependent variables for both RMI and DMI. The results indicate that a dependence of both indicators on their own past values exists. However, the coefficient size differs as the coefficient ranges at ~0.6 for RMI (Table 4), while it is at ~0.8 for DMI (Table 5).

To capture the scale of the economy, we include the contemporaneous GDP. For RMI, we find that GDP is significant with a coefficient of ~.6, indicating that a 1% increase in GDP raises the RMI by 0.6%.[81] Turning to specifications with DMI as dependent variable, we find that the coefficient of GDP is slightly significant in the AB estimation with a coefficient roughly half as large as for RMI. This finding further holds when looking at the coefficients of GDP in Table 4 and 5. As for RMI, it fluctuates between 0.38 and 0.65, while it remains slightly significant or insignificant for DMI. This result appears plausible, given the potential relevance of the outsourcing of material intensive production steps (Schaffartzik et al., 2016), which is not sufficiently captured in the DMI indicator. Thus, it seems reasonable that the impact of GDP is larger when accounting for upstream flows.

To capture structural change, considered highly relevant in determining material flows (Steger and Bleischwitz, 2011; Weisz et al., 2006), we include the share of the industry sector in the value added of a country (Industrial Intensity). The results concerning Industrial Intensity remain somewhat inconclusive. For RMI (Table 4), it is only significant in two specifications with a coefficient of 0.35 and 0.52 respectively. For DMI (Table 5), it is found to be significant in three estimations with a coefficient size of ~.3 to ~.8. These coefficients can be interpreted as stating that a one percentage point increase in the industrial sectors share is associated with a ~0.3 to ~0.8% increase in material usage. These results are in line with the consideration that the industrial sector's comparatively high resource intensity becomes smaller as the material intensity of the service sector rises when upstream interlinkages are taken into account (Steger and Bleischwitz, 2011). This is given in the RMI indicator.

We now turn to look at model estimations dealing with the more specific classifications of green technologies by technological domain. As discussed earlier we specify alternative energy

[81] This value represents the short-run coefficient, and the same goes for all other regressor coefficients. As the dependent variable follows an autoregressive process defined by the coefficient on the LDV, the impact of changes in a regressor in t affects not only the dependent variable in t, but also in coming periods. The long-run coefficients can be computed dividing each short-run coefficient by one minus the sum of the coefficients on the lag of the dependent variable (Pesaran and Smith, 1995).

production (EI_AEP), transportation (EI_Transp), recycling and reuse (EI_Recy), energy efficiency (EI_EnEff), and climate change mitigation in the production or processing of goods (EI_ProGo). The results using RMI as dependent variable are shown in Table 4.

Table 4: Results of Different EI domains for Raw Material Input

	(1)	(2)	(3)	(4)	(5)	(6)
Model	AB	AB	AB	AB	AB	AB
Dep. Var.	Raw Material Input	Raw Material Input	Raw Material Input	Raw Material Input	Raw Material Input	Raw Material Input
L1. Raw Material Input	0.378*	0.629***	0.708***	0.674***	0.558***	0.640***
	(0.193)	(0.106)	(0.172)	(0.124)	(0.130)	(0.124)
EI_Full	-0.0105					
	(0.0335)					
EI_AEP		-0.0239				
		(0.0171)				
EI_Transp			-0.0563			
			(0.0353)			
EI_Recy				-0.0482***		
				(0.0128)		
EI_EnEff					-0.0370**	
					(0.0177)	
EI_ProGo						-0.0224
						(0.0153)
GDP	0.584***	0.494***	0.391**	0.440***	0.645***	0.381*
	(0.202)	(0.175)	(0.177)	(0.159)	(0.215)	(0.195)
Industrial Intensity	0.602	0.227	0.321	0.347*	0.208	0.519**
	(0.407)	(0.218)	(0.280)	(0.200)	(0.262)	(0.201)
Time-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	532	512	485	486	502	483
No. of Countries	27	27	26	27	27	27
No. of Instruments	36	36	36	36	36	36
AR1-Test	-2.25	-2.87	-2.44	-2.63	-2.60	-2.78
	[0.024]	[0.004]	[0.015]	[0.009]	[0.009]	[0.005]
AR2-Test	0.86	0.58	0.82	0.44	0.59	0.47
	[0.389]	[0.560]	[0.414]	[0.661]	[0.557]	[0.636]
Sargan-Test	18.67	15.67	16.28	12.34	14.11	19.03
	[0.067]	[0.154]	[0.131]	[0.338]	[0.227]	[0.061]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

More specific definitions of EI lead to differing results compared to the holistic definition of EI_Full. In the cases of EI_AEP, EI_Transp, and EI_ProGo, EI remains insignificant, although the coefficient size gets larger in magnitude. Innovation in the areas of EI_Recy, and EI_EnEff are found to significantly reduce material usage. The largest effect in magnitude can be found for EI_Recy as a 1% increase in the knowledge stock is associated with a ~0.05% decrease of material usage, significant at a 1% level. EI_EnEff is significant at a 5% level with a smaller coefficient, indicating a ~0.04% decrease of material usage per percentage increase of the knowledge stock.

Now we turn to the same estimations with DMI as our dependent variable. The results are reported in Table 5. It can be noted that the results for our different EI fields are qualitatively similar with our results for RMI. EI_AEP, EI_Transp, and EI_ProGo remain insignificant. EI_Recy is found to be significant at a 5% level, with a coefficient smaller in magnitude. The coefficient of EI_EnEff is larger in magnitude, significant at a 10% level.

Table 5: Results of Different EI domains for Direct Material Input

	(1)	(2)	(3)	(4)	(5)	(6)
Model	AB	AB	AB	AB	AB	AB
Dep. Var.	Direct Material Input	Direct Material Input	Direct Material Input	Direct Material Input	Direct Material Input	Direct Material Input
L1. Direct Material Input	0.800***	0.796***	0.795***	0.814***	0.715***	0.761***
	(0.0696)	(0.0874)	(0.112)	(0.105)	(0.108)	(0.0893)
EI_Full	-0.0203					
	(0.0184)					
EI_AEP		-0.0242				
		(0.0153)				
EI_Transp			-0.0562			
			(0.0358)			
EI_Recy				-0.0389**		
				(0.0162)		
EI_EnEff					-0.0402*	
					(0.0201)	
EI_ProGo						-0.0240
						(0.0148)
GDP	0.276*	0.307*	0.287*	0.224	0.415*	0.190
	(0.141)	(0.156)	(0.151)	(0.152)	(0.234)	(0.172)
Industrial Intensity	0.316*	0.297	0.422	0.542**	0.425	0.831***
	(0.183)	(0.229)	(0.357)	(0.240)	(0.282)	(0.181)
Time-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	532	512	485	486	502	483
No. of Countries	27	27	26	27	27	27
No. of Instruments	36	36	36	36	36	36
AR1-Test	-3.56	-3.46	-3.11	-3.25	-3.40	-3.47
	[0.000]	[0.001]	[0.002]	[0.001]	[0.001]	[0.001]
AR2-Test	-0.06	0.21	0.15	0.03	0.22	0.20
	[0.955]	[0.837]	[0.878]	[0.974]	[0.825]	[0.840]
Sargan-Test	11.59	14.13	9.35	9.20	11.16	12.70
	[0.395]	[0.226]	[0.589]	[0.603]	[0.430]	[0.313]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Even though the links of EI with material usage are statistically strong, the estimated elasticities are rather small, ranging between -0.0482 and -0.0370. However, to assess the effect of EI on material usage, these numbers need to be seen in the context of the overall change of EI, as even small elasticities may indicate a large effect if the changes in EI are large (see also Costantini et al., 2017). To calculate the average effect of EI on material usage in a given year we multiply the elasticities with the average changes of the EI variables. The average increase in knowledge in a given year for EI_Recy is associated with a reduction of material usage by 0.57 percent with respect to RMI. EI_EnEff entails a similar impact on RMI with a reduction of 0.54 percent. For DMI, EI_EnEff has a larger effect with a reduction of 0.59 percent, whereas EI_Recy reduces material usage by 0.46 percent in a given year. Recalling that the average increases of RMI and DMI are about 3 percent and 1.4 percent respectively (Section 4.1.), these technology effects account for a relevant reduction of material usage.

These results indicate that the effects of innovation on material usage differ based on technological domain. However, utilizing patent data can result in including too many or too few patents into the classification. An overestimation of the patent stock mainly results in a heightened risk of not finding a significant parameter (even if the true parameter is significant), while underestimating the knowledge stock limits conclusions for the technologies included (Wurlod and Noailly, 2016). To secure that we have isolated an actual effect of the specific green technological domains that does not stem from mistakes in our technology boundary, we now test variables found to be significant by analyzing their non-green counterparts and total innovations (Total Inno) in our model. The results are shown in Table 6.

Table 6: Results for Non-green Technologies for Raw Material Input

	(1)	(2)	(3)	(4)	(5)	(6)
Model	AB	AB	AB	AB	AB	AB
Dep. Var.	Raw Material Input	Raw Material Input	Raw Material Input	Direct Material Input	Direct Material Input	Direct Material Input
L1. Raw Material Input	0.554***	0.552***	0.552***			
	(0.158)	(0.155)	(0.159)			
L1. Direct Material Input				0.863***	0.862***	0.866***
				(0.0652)	(0.0655)	(0.0647)
Total Inno	-0.0233			-0.0188		
	(0.0206)			(0.0173)		
NG_EnEff		-0.0230			-0.0191	
		(0.0206)			(0.0169)	
NG_Recy			-0.0232			-0.0176
			(0.0210)			(0.0169)
GDP	0.488***	0.487***	0.489***	0.195	0.197	0.187
	(0.161)	(0.156)	(0.165)	(0.124)	(0.122)	(0.124)
Industrial Intensity	0.485**	0.490**	0.487**	0.321**	0.322**	0.324**
	(0.227)	(0.229)	(0.229)	(0.145)	(0.145)	(0.144)
Time-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	532	532	532	532	532	532
No. of Countries	27	27	27	27	27	27
No. of Instruments	38	38	38	35	35	35
AR1-Test	-2.73	-2.75	-2.70	-3.69	-3.68	-3.70
	[0.006]	[0.006]	[0.007]	[0.000]	[0.000]	[0.000]
AR2-Test	0.84	0.84	0.84	-0.10	-0.10	-0.10
	[0.400]	[0.399]	[0.400]	[0.919]	[0.919]	[0.917]
Sargan-Test	19.29	19.17	19.32	11.76	11.65	11.97
	[0.114]	[0.118]	[0.113]	[0.301]	[0.309]	[0.287]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

The results show that neither general innovation (Total Inno) nor the non-green counterparts of the EI domains have a significant impact on material usage.[82] This indicates that the EI domains

[82] Note that for reporting sound and homogenous specifications, we instrumented all innovation variables with lag three and four. For RMI we allowed lags two to thirteen for the LDV. Results are not sensitive to different instrumentation choices.

have a specific effect on material usage that is different from overall technology effects. This result holds for both RMI and DMI. Hence, we are confident that we have identified an effect of our specific measures of green technology, which is sensitive to the fact that general innovation is not associated with decreases in material usage. This renders a plausible impression that our finding of EI_Full to be insignificant is due to the inclusion of certain technological areas which are unrelated to a reduction of material usage.

4.6.2 Robustness Checks

We will proceed by checking the robustness of the obtained results of EI. First, we will include additional explanatory variables that are considered to be potentially relevant determinants of material usage. Then we will reduce the instruments in our AB modelling, so that we use almost as many instruments as there are countries in our sample (Roodman, 2009). Hereby, we ensure that the results are not sensitive to the number of instruments used. The results for the inclusion of control variables are reported in Tables A3a to A3d in the Appendix. The reduction of the instruments is reported in Table A3e.

We analyze variables concerning trade openness, i.e., the embeddedness of the country in the world economy (Carattini et al., 2015), population (Krausmann et al., 2009), the share of urban population (Shao et al., 2017), and energy composition (Weisz et al., 2006) proxied by the share of renewable energy in TPES. All variables are in natural logarithm or share. The share of renewable energy was included in first-differences as the stationarity test (see Appendix Table A2) indicated that this variable is non-stationary in levels.

Trade openness is often considered to be relevant for countries' environmental damage (Carattini et al., 2015). It may reflect competitive pressure as the world market forces countries' industries to be more resource efficient (Steger and Bleischwitz, 2011; Voet et al., 2005). Trade openness may also be related to structural implications (Carattini et al., 2015). However, our results show trade openness to be insignificant. An explanation could be that embeddedness in the world market also means increased supply and availability of resources.

Population is a highly relevant determinant of environmental damage, which is reflected both in the material flow literature and the IPAT hypothesis (amongst others, Krausmann et al., 2009; Steinberger et al., 2010; Weina et al., 2016). We find population to be insignificant, which seems mainly due to our estimation analyzing changes in material usage. Absolute changes in economic activity are captured in GDP, and population has a low variance in industrialized countries anyhow (Weina et al., 2016).

We check for the share of urban population as a proxy for the population prone to live according to a typical industrial metabolic profile (Shao et al., 2017). Our findings show this variable to be insignificant, which may be due to our application looking at material input in contrast to other analyses (Shao et al., 2017), as well as high density settlements reducing the per capita infrastructural requirements (Weisz et al., 2006).

The composition of the energy supply is often considered to influence material usage (Steger and Bleischwitz, 2011; Weisz et al., 2006), as renewable energy may reduce the usage of, e.g., fossil fuels. The insignificance of this variable in our analysis may be due to the additional material demand required to set up renewable energy infrastructures (Steger and Bleischwitz, 2011). Another possible reason for this insignificance could be due to the fact that we do not explore cross-country differences, but rather focus on changes within individual countries. Furthermore, renewable energy likely captures a substitution among materials (Bithas and Kalimeris, 2017), while we analyze total material usage.

Now we turn to the reductions of the instrument count. We reduce the used lags of the innovation variable and the GDP variable to only the second lag as an instrument. The instruments for the LDV were reduced to lag two to six.[83] We find that the results concerning EI_Recy remain rather robust. EI_Recy remains significant both for RMI and DMI at the 5% and 10% level respectively. The coefficient turns a little smaller in magnitude. EI_EnEff shows to be more sensitive. Both for RMI and DMI the coefficient loses its significance. While the coefficient turns larger in magnitude for RMI, it turns substantially smaller in magnitude in the case of DMI.

4.6.3 Discussion

This paper contributes mainly to the debate on the environmental effects of environmental innovation (EI). Unlike previous work we have constructed indicators of material usage to operationalize environmental impact. We have focused on both Direct Material Input (DMI) and Raw Material Input (RMI) to account for the respective shortcomings that both indicators present. The role of EI was explored in more detail by defining subclasses that represent different areas of green technological change.

[83] To secure a sound estimation concerning, e.g., the coefficient of the LDV.

As discussed in Section 2, previous work focused on other indicators of environmental pressure when assessing the effects of EI, mainly emission indicators. On the sectoral level, reducing effects of EI were found (Carrión-Flores and Innes, 2010; Costantini et al., 2017; Ghisetti and Quatraro, 2017; Wurlod and Noailly, 2016), while on the regional level evidence was more inconclusive (Wang et al., 2012; Weina et al., 2016; Zhang et al., 2017). The work most related to our sample of European countries is the analysis of eco-innovation effects in European sectors. Here a direct and indirect effect of EI is found, as effects occur not only in the sector where an EI originates, but also in other sectors through market transactions (Costantini et al., 2017). Such a supply chain effect is captured on a national level to some extent. Moreover, EI activities are embedded in the general national effort to upgrade the sustainability of its production (Costantini et al., 2017). On the national level, spillovers between regions are included, which are considered a channel through which EI exerts its effects (Barbieri et al., 2016).

A further contribution of this paper concerns the subdomains of EI we defined to explore various areas affecting material usage in different ways. Our findings suggest that green innovation in the areas of energy efficiency (EI_EnEff), and recycling and reuse (EI_Recy) is associated with decreases in material usage. Such effects could not be found for the EI domains of alternative energy production (EI_AEP), transportation (EI_Transp), climate change mitigation in the production or processing of goods (EI_ProGo), and overall EI (EI_Full). Energy efficiency measures can be considered to affect material usage rather directly as reduced energy demand results in associated decreases in the utilization of materials like fossil fuels or other energy carriers. A similar consideration can be applied to technological advances in recycling and reusing, as they decrease the need for newly extracted materials, and promote the concept of a circular economy (Cullen, 2017; European Commission, 2015).

EI in the production or processing of goods includes a broad range of technologies listed in the Y02P class. As these technologies strongly relate to resource-intensive production processes, they likely capture not only direct effects (e.g., recycling or energy efficiency measures), but also the general innovative effort to upgrade the sustainability of production and processing. Hence, the fact that this EI domain is found insignificant could be related to the inclusion of technologies unrelated to reductions of material usage, and the arising difficulty with isolating the reducing effect (see Wurlod and Noailly, 2016). Concerning our measures of EI_AEP and EI_Transp, which were also found to be insignificant, two further interpretations can be considered. First, both EI_AEP and EI_Transp capture technologies which are basically related to the substitution of materials, not specifically their reduction. It remains uncertain which type of environmental pressures will arise due to the utilization of new technologies, such as electric mobility (Hepburn et al., 2018). Hence, the effects of these technologies can potentially not be sufficiently captured by our aggregated material indicators. For example, the utilization of solar energy may reduce fossil demand but, on the other hand, increase the need for specific metals or other materials as new infrastructural requirements emerge. The same seems to hold for new modes of transportation. Second, an alternative and complementary explanation concerns the empirical framework. While changes in reusing materials in industrial processes are rather quickly implementable, redefining the energy supply system or the transportation system are large scale technological and societal processes.[84] Hence, policy may play a more important role in facilitating these changes (Popp et al., 2011). Capturing them in an empirical setting seems more difficult due to the uncertain time-horizon of such transformations.

Thus, while some specific EI domains are found to reduce material usage, such results can neither be obtained for general innovation nor the non-green counterparts of our EI domains. These findings point to the relevance of narrowly defining technological areas. While some technological domains within the broad definition of EI (EI_Full) exert an effect, this effect cannot be isolated for our broad definition of EI as the inclusion of technologies that do not affect material usage (e.g., water technologies) likely causes finding no impact of general EI (Wurlod and Noailly, 2016). Although we do not find an impact of general innovation or non-green subgroups, there likely are “non-green” technologies that reduce material usage. Generally, it is considered that many “normal” innovations do provide environmental improvements (Kemp and Pearson, 2007). Especially in the context of material usage, we could expect such results. Improving efficiency and reducing costly materials can be considered as general aims of innovative activity that strives to enable general productivity gains. Thus, the fact that all non-green groups and general innovation were found to be insignificant should be interpreted cautiously in the sense that our EI domains exert a different effect than overall innovation.

With a focus on material usage, our results also provide further evidence contributing to the literature on decoupling.[85] We explicitly operationalize the impact of green technologies and assess both the impacts on RMI and DMI. The fact that there is a reducing impact of EI on

[84] Especially the societal aspect in these technological changes should be stressed. As soon as changes no longer just occur “behind the curtain” of production facilities and firms, but enter directly in the life and daily environment of people there can be a high degree of resistance causing such changes to turn into difficult and long-lasting societal negotiation processes, making it difficult to capture such aspects in an empirical setting as used in the proposed analysis.

[85] Please note that given the empirical design the interpretation of the results in the sense of decoupling should be treated with caution, due to the presence of the LDV and time-effects (Plümper et al., 2005).

material usage, points to the notion that at least a relative decoupling is likely as we ascertain a technology effect (Bithas and Kalimeris, 2017; Stern, 2004; UNEP, 2011). Referring to Table 4 and 5, it is obvious that GDP plays a role in determining material use. We observe a substantial and robust impact of GDP on RMI. For DMI, we find the influence of GDP to be more modest. Our observations concur with the consideration that European countries have profited - with respect to their DMI - from the outsourcing of material intensive activities through international trade. Therefore, resource efficiency gains may be substantially smaller when accounting for upstream flows (Schaffartzik et al., 2016; Wiedmann et al., 2015). The effects of structural change, which are more pronounced for DMI, support these observations. Nonetheless, our results show for both indicators that EI can contribute to reductions in material usage. Thus, strengthening EI seems a valid way to reduce the material usage in European economies. Reductions by technology need to be kept from being overwhelmed by rebound effects and continued economic growth (Binswanger, 2001; Freire-González, 2017) if an absolute reduction of environmental impact is to be achieved.

4.7 Conclusions

A reduction of material usage has become an important goal on the political agenda (European Commission, 2011a). The aim of this paper was to empirically examine the effects that environmental innovation (EI) had on material usage within the European Union countries. Input indicators based on the methodology of Material Flow Accounting have been considered as more holistic proxies of environmental pressure (Agnolucci et al., 2017; Fischer-Kowalski et al., 2011) than single-pressure indicators such as CO_2 emissions.

We provide new evidence that EI has contributed to reductions of material usage in European economies. For technologies in the areas of energy efficiency, and recycling and reuse, we find that EI did contribute to such reductions. For further classifications of technologies, we do not find significant effects on material usage. This could, however, be due to issues of capturing substitutions between materials, long time-horizons in systemic technological change, as well as too broad definitions of technological fields. These results have important implications for academics and policymakers alike, as substantial differences in the effects of technologies occur. Differences in feasibility, time requirements for changes, and overall environmental effects of technologies need to be accounted for in order to facilitate effective policies and an appropriate analysis of green technological change. Nonetheless, our main results complement earlier findings on the effects of EI on emissions and energy intensity (Carrión-Flores and Innes, 2010; Costantini et al., 2017; Ghisetti and Quatraro, 2017; Wurlod and Noailly, 2016; Zhang et al., 2017), although the comparability of studies remains limited, given the differences in indicators, samples and econometric methods.

Differences between the two input indicators have been found. For both RMI and DMI, there is a technology effect, as for both indicators EI is found to have a significant reducing effect. Scale effects are found to be more relevant in the case of RMI. Effects of structural change are more pronounced for DMI.[86] Thus, our results support considerations present in decoupling literature suggesting that successes in decoupling may be biased upwards due to outsourcing via international trade (Schaffartzik et al., 2016; Steger and Bleischwitz, 2011; Wiedmann et al., 2015).

Some further avenues of research emerge from the limitations of this analysis. First, the analysis could be refined by unpacking material classes to identify substitutional effects among materials (Bithas and Kalimeris, 2017). A more detailed analysis focusing on a sectoral level (Costantini et al., 2017) might identify the potential of EI in material usage reduction in different sectors. Generally, our results support the relevance of looking at specific technological domains and of accounting for effects along entire supply chains. Hence, there is a need for research that provides an in-depth analysis of the holistic effects of specific green technologies. Given the crucial relevance of scale effects in driving material usage, especially the political dimension needs to be taken into account when striving towards Sustainable Development. This involves the relevance of public policy and governance to support the development and spreading of green technologies, but also the key issue of avoiding rebound effects and growth as a consequence of technological progress (Aghion and Howitt, 1998; Binswanger, 2001; Freire-González, 2017). If these are not sufficiently accounted for, the merits of EI are likely eaten up or even overcompensated for by scale effects.

Despite these limitations, our results support the notion that environmental innovation can contribute to reducing material usage. Therefore, supporting environmental innovation and reducing environmentally harmful subsidies (Wilts and O'Brien, 2019) could create a win-win situation. However, the holistic impacts of innovation should be taken into account, such as the long-term induced dynamics of EI, when being dealt with at the political level.

While the potential of environmental innovation to reduce environmental pressure may be far from being fully exploited, it cannot be ignored that technological advances have not as yet

[86] It should be noted that the empirical analysis does not allow for conclusions on the effects of structural change on specific material classes.

been able to solve our environmental issues. Rather, these issues tend to become more and more pressing. Simply hoping for future technological breakthroughs to solve our issues, would be unreasonable, if not reckless. Especially, given the limitations on decoupling (Cullen, 2017; Georgescu-Roegen, 1971; Meadows et al., 1972; Schramski et al., 2015), the pursuit of Sustainable Development calls for continuous adjustment and alignment with environmental necessities. Fundamental changes in lifestyles and societal structures may become inevitable and should be strengthened as required, in order to not realize too late that technology may not do the trick.

Appendix

Table A1: Descriptive Statistics

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max	Source
Total Raw Material Input (RMI)	Tons	588	4.84e+08	5.92e+08	7421426	2.38e+09	UN Environment International Resource Panel Global Material Flows Database
Total Direct Material Input (DMI)	Tons	588	3.15e+08	3.60e+08	5162637	1.50e+09	UN Environment International Resource Panel Global Material Flows Database
Industrial Intensity: Sector Share in Gross Value Added	Share	620	.283	.059	.113	.524	Cambridge Econometrics European Regional Database (ERD)
GDP	Billions of Euro	620	384.00	601.25	2.80	2539.85	Cambridge Econometrics European Regional Database (ERD)
EI_Full	Stock	621	1449.74	3868.92	0	32174.14	PATSTAT 2017b
EI_AEP	Stock	621	521.25	1285.04	0	10342.2	PATSTAT 2017b
EI_Transp	Stock	621	192.04	614.47	0	6008.21	PATSTAT 2017b
EI_Recy	Stock	621	83.07	194.10	0	1309.30	PATSTAT 2017b
EI_EnEff	Stock	621	285.89	768.56	0	7326.65	PATSTAT 2017b
EI_ProGo	Stock	621	114.72	295.39	0	2658.38	PATSTAT 2017b
Total Inno	Stock	621	8541.33	21704.97	.43	167442.2	PATSTAT 2017b
NG_EnEff	Stock	621	8255.44	20948.14	.43	160115.5	PATSTAT 2017b
NG_Recy	Stock	621	8458.26	21515.21	0	166132.9	PATSTAT 2017b
NG_ProGo	Stock	621	8426.61	21411.78	.43	164783.8	PATSTAT 2017b
Trade Openness[87]	Share	600	1.00	.56	.34	3.44	World Bank
Population	Thousand people	620	17918	22227	360	82520	Cambridge Econometrics European Regional Database (ERD)
Renewable Energies in Total Primary Energy Supply	Share	621	.087	.084	0	.374	OECD
Urban Population	Share	621	.717	.117	.479	.977	World Bank

[87] Trade Openness is equivalent to the sum of Imports/GDP and Exports/GDP.

Table A2: Unit Roots

	Fisher ADF Inv. X2	**Fisher ADF** Inv. N	**Fisher ADF** Inv. L	**Fisher ADF** M. Inv. X2
Total Raw Material Input (RMI)	135.94 [0.0000]	-6.98 [0.0000]	-6.87 [0.0000]	7.89 [0.0000]
Total Direct Material Input (DMI)	137.44 [0.0000]	-6.95 [0.0000]	-6.91 [0.0000]	8.03 [0.0000]
Industrial Intensity: Sector Share in Gross Value Added	161.00 [0.0000]	-6.67 [0.0000]	-7.44 [0.0000]	10.30 [0.0000]
GDP	141.96 [0.0000]	-7.03 [0.0000]	-7.14 [0.0000]	8.46 [0.0000]
EI_Full	128.59 [0.0000]	-4.95 [0.0000]	-5.55 [0.0000]	7.18 [0.0000]
EI_AEP	109.03 [0.0000]	-4.15 [0.0000]	-4.46 [0.0000]	5.30 [0.0000]
EI_Transp	67.65 [0.0488]	-0.98 [0.1625]	-0.86 [0.1954]	1.77 [0.0388]
EI_Recy	120.24 [0.0000]	-4.87 [0.0000]	-5.12 [0.0000]	6.37 [0.0000]
EI_EnEff	94.28 [0.0006]	-1.84 [0.0325]	-1.85 [0.0333]	3.88 [0.0001]
EI_ProGo	126.60 [0.0000]	-4.35 [0.0000]	-5.21 [0.0000]	6.99 [0.0000]
Total Inno	180.35 [0.0000]	-7.94 [0.0000]	-8.90 [0.0000]	12.16 [0.0000]
NG_EnEff	175.73 [0.0000]	-7.73 [0.0000]	-8.61 [0.0000]	11.71 [0.0000]
NG_Recy	173.44 [0.0000]	-7.54 [0.0000]	-8.45 [0.0000]	11.49 [0.0000]
NG_ProGo	177.68 [0.0000]	-7.74 [0.0000]	-8.69 [0.0000]	11.90 [0.0000]
Trade Openness	103.54 [0.0001]	-4.60 [0.0000]	-4.56 [0.0000]	4.77 [0.0000]
Population	122.37 [0.0000]	-2.55 [0.0053]	-3.40 [0.0004]	6.58 [0.0000]
Renewable Energies in Total Primary Energy Supply	45.89 [0.7760]	2.95 [0.9984]	3.31 [0.9994]	-0.78 [0.7825]
***Δ* Renewable Energies in Total Primary Energy Supply**	257.55 [0.0000]	-11.65 [0.0000]	-13.48 [0.0000]	19.59 [0.0000]
Urban Population	152.76 [0.0000]	-2.34 [0.0098]	-3.30 [0.0006]	9.50 [0.0000]

Variables used are in logarithm or share.

Fisher-ADF: *The Fisher-type unit-root tests are based on augmented Dickey–Fuller (Fisher-ADF) tests with drift and one lag; the null hypothesis is that "all panels contain unit-roots"; the test does not require a balanced panel. Statistics and respective p-values (in square brackets) are reported for each type of Fisher test: inverse chi-squared, inverse normal, inverse logit and modified inverse chi-squared.*

Δ is the first difference operator.

Table A3a: Inclusion of Controls for RMI / EI_EnEff

	(1)	(2)	(3)	(4)	(5)
Model	AB	AB	AB	AB	AB
Dep. Var.	Raw Material Input	Raw Material Input	Raw Material Input	Raw Material Input	Raw Material Input
L1. Raw Material Input	0.569***	0.611***	0.561***	0.573***	0.638***
	(0.127)	(0.0932)	(0.132)	(0.117)	(0.103)
EI_EnEff	-0.0399	-0.0437*	-0.0369**	-0.0389*	-0.0446*
	(0.0237)	(0.0230)	(0.0179)	(0.0193)	(0.0261)
GDP	0.680**	0.610***	0.640***	0.629***	0.593**
	(0.303)	(0.199)	(0.219)	(0.214)	(0.289)
Industrial Intensity	0.177	0.110	0.211	0.178	0.0849
	(0.287)	(0.360)	(0.263)	(0.258)	(0.366)
Trade Openness	-0.0243				-0.0140
	(0.0330)				(0.0316)
Population		-0.143			-0.129
		(0.229)			(0.223)
D1. Renewable Energy			-0.117		-0.170
			(0.219)		(0.219)
Urban Population				-0.236	-0.189
				(0.286)	(0.283)
Time-effects	Yes	Yes	Yes	Yes	Yes
Observations	500	502	502	502	500
No. of Countries	27	27	27	27	27
No. of Instruments	37	37	37	37	40
AR1-Test	-2.72	-2.81	-2.59	-2.69	-2.91
	[0.007]	[0.005]	[0.010]	[0.007]	[0.004]
AR2-Test	0.60	0.60	0.62	0.59	0.65
	[0.548]	[0.550]	[0.536]	[0.555]	[0.515]
Sargan-Test	14.41	14.66	14.15	14.29	15.22
	[0.211]	[0.199]	[0.225]	[0.217]	[0.172]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Table A3b: Inclusion of Controls for RMI / EI_Recy

	(1)	(2)	(3)	(4)	(5)
Model	AB	AB	AB	AB	AB
Dep. Var.	Raw Material Input	Raw Material Input	Raw Material Input	Raw Material Input	Raw Material Input
L1. Raw Material Input	0.680***	0.713***	0.681***	0.692***	0.720***
	(0.107)	(0.126)	(0.122)	(0.114)	(0.104)
EI_Recy	-0.0465***	-0.0497***	-0.0479***	-0.0482***	-0.0467***
	(0.0127)	(0.0135)	(0.0124)	(0.0137)	(0.0129)
GDP	0.412**	0.414**	0.428***	0.412**	0.356**
	(0.150)	(0.155)	(0.154)	(0.157)	(0.140)
Industrial Intensity	0.362*	0.256	0.355*	0.317	0.276
	(0.188)	(0.296)	(0.195)	(0.200)	(0.260)
Trade Openness	0.00986				0.0174
	(0.0201)				(0.0206)
Population		-0.124			-0.0863
		(0.220)			(0.193)
D1. Renewable Energy			-0.159		-0.188
			(0.196)		(0.193)
Urban Population				-0.228	-0.239
				(0.212)	(0.193)
Time-effects	Yes	Yes	Yes	Yes	Yes
Observations	486	486	486	486	486
No. of Countries	27	27	27	27	27
No. of Instruments	37	37	37	37	40
AR1-Test	-2.67	-2.65	-2.65	-2.70	-2.72
	[0.008]	[0.008]	[0.008]	[0.007]	[0.006]
AR2-Test	0.43	0.44	0.47	0.44	0.46
	[0.667]	[0.659]	[0.641]	[0.662]	[0.642]
Sargan-Test	12.34	11.53	12.19	12.13	11.25
	[0.339]	[0.400]	[0.350]	[0.354]	[0.423]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Table A3c: Inclusion of Controls for DMI / EI_EnEff

	(1)	(2)	(3)	(4)	(5)
Model	AB	AB	AB	AB	AB
Dep. Var.	Direct Material Input	Direct Material Input	Direct Material Input	Direct Material Input	Direct Material Input
L1. Direct Material Input	0.724***	0.742***	0.718***	0.718***	0.755***
	(0.0948)	(0.0914)	(0.109)	(0.106)	(0.0912)
EI_EnEff	-0.0443	-0.0458*	-0.0400*	-0.0410*	-0.0491
	(0.0302)	(0.0236)	(0.0201)	(0.0202)	(0.0296)
GDP	0.468	0.415*	0.406*	0.411*	0.448
	(0.373)	(0.224)	(0.237)	(0.236)	(0.362)
Industrial Intensity	0.378	0.316	0.432	0.410	0.276
	(0.309)	(0.345)	(0.281)	(0.289)	(0.391)
Trade Openness	-0.0315				-0.0252
	(0.0564)				(0.0565)
Population		-0.128			-0.132
		(0.212)			(0.225)
D1. Renewable Energy			-0.312		-0.352
			(0.341)		(0.324)
Urban Population				-0.111	-0.0225
				(0.306)	(0.301)
Time-effects	Yes	Yes	Yes	Yes	Yes
Observations	500	502	502	502	500
No. of Countries	27	27	27	27	27
No. of Instruments	37	37	37	37	40
AR1-Test	-3.58	-3.49	-3.41	-3.43	-3.57
	[0.000]	[0.000]	[0.001]	[0.001]	[0.000]
AR2-Test	0.23	0.23	0.27	0.22	0.29
	[0.818]	[0.821]	[0.786]	[0.824]	[0.774]
Sargan-Test	9.67	10.89	11.24	11.09	9.13
	[0.561]	[0.452]	[0.423]	[0.436]	[0.610]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Table A3d: Inclusion of Controls for DMI / EI_Recy

	(1)	(2)	(3)	(4)	(5)
Model	AB	AB	AB	AB	AB
Dep. Var.	Direct Material Input	Direct Material Input	Direct Material Input	Direct Material Input	Direct Material Input
L1. Direct Material Input	0.825***	0.841***	0.822***	0.817***	0.849***
	(0.0926)	(0.0989)	(0.104)	(0.104)	(0.0837)
EI_Recy	-0.0367**	-0.0404**	-0.0389**	-0.0392**	-0.0381**
	(0.0175)	(0.0165)	(0.0158)	(0.0163)	(0.0172)
GDP	0.189	0.217	0.209	0.217	0.170
	(0.166)	(0.136)	(0.150)	(0.157)	(0.148)
Industrial Intensity	0.551**	0.424	0.548**	0.527**	0.449
	(0.242)	(0.325)	(0.234)	(0.249)	(0.307)
Trade Openness	0.00905				0.0150
	(0.0256)				(0.0263)
Population		-0.125			-0.100
		(0.200)			(0.185)
D1. Renewable Energy			-0.430		-0.444
			(0.305)		(0.313)
Urban Population				-0.0998	-0.0983
				(0.234)	(0.217)
Time-effects	Yes	Yes	Yes	Yes	Yes
Observations	486	486	486	486	486
No. of Countries	27	27	27	27	27
No. of Instruments	37	37	37	37	40
AR1-Test	-3.26	-3.26	-3.29	-3.26	-3.31
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
AR2-Test	0.02	0.04	0.08	0.03	0.07
	[0.984]	[0.971]	[0.936]	[0.974]	[0.941]
Sargan-Test	9.11	8.41	8.77	9.05	7.79
	[0.611]	[0.676]	[0.643]	[0.617]	[0.732]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Table A3e: Reductions of the Instrument Count

	(1)	(2)	(3)	(4)
Model	AB	AB	AB	AB
Dep. Var.	Raw Material Input	Raw Material Input	Direct Material Input	Direct Material Input
L1. Raw Material Input	0.501**	0.676***		
	(0.211)	(0.167)		
L1. Direct Material Input			0.847***	0.844***
			(0.112)	(0.118)
EI_EnEff	-0.0492		-0.0224	
	(0.0371)		(0.0193)	
EI_Recy		-0.0449**		-0.0323*
		(0.0191)		(0.0178)
GDP	0.749*	0.441	0.173	0.179
	(0.401)	(0.273)	(0.220)	(0.217)
Industrial Intensity	0.196	0.338	0.421**	0.531**
	(0.297)	(0.245)	(0.203)	(0.224)
Time-effects	Yes	Yes	Yes	Yes
Observations	502	486	502	486
No. of Countries	27	27	27	27
No. of Instruments	29	29	29	29
AR1-Test	-2.02	-2.50	-3.47	-3.34
	[0.043]	[0.012]	[0.001]	[0.001]
AR2-Test	0.58	0.44	0.12	0.02
	[0.559]	[0.663]	[0.903]	[0.985]
Sargan-Test	5.64	5.50	4.63	3.73
	[0.228]	[0.240]	[0.328]	[0.443]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

A4: Technology Classes of Specific EI Domains

List 1: Alternative Energy Production

IPC	IPC	IPC	IPC	CPC
A01H	C12N 9/32	F21S 9/03	H01M 14/	Y02E 10/
A62D 3/02	C12N 9/34	F22B 1/	H01M 2/02	Y02E 50/
B01D 53/	C12N 9/36	F23B 90/	H01M 2/04	Y02E 20/
B09B	C12N 9/38	F23G 5/	H01M 4/86	
B60K 16/	C12N 9/40	F23G 7/	H01M 4/87	
B60L 8/	C12N 9/42	F24D 11/	H01M 4/88	
B63B 35/	C12N 9/44	F24D 15/04	H01M 4/89	
B63H 13/	C12N 9/46	F24D 17/	H01M 4/90	
B63H 19/02	C12P 5/02	F24D 19/	H01M 4/91	
B63H 19/04	C12P 7/06	F24D 3/	H01M 4/92	
C01B 33/02	C12P 7/07	F24D 5/	H01M 4/93	
C01B 33/03	C12P 7/08	F24F 12/	H01M 4/94	
C02F 1/14	C12P 7/09	F24F 5/	H01M 4/95	
C02F 1/16	C12P 7/10	F24H 4/	H01M 4/96	
C02F 11/04	C12P 7/11	F24S	H01M 4/97	
C02F 11/14	C12P 7/12	F24T	H01M 4/98	
C02F 3/28	C12P 7/13	F24V 30/	H01M 8/	
C02M 1/107	C12P 7/14	F24V 40/	H02J 7/35	
C02M 1/113	C12P 7/64	F24V 50/	H02K 7/18	
C07C 67/	C21B 5/06	F25B 27/	H02N 10/	
C07C 69/	C23C 14/14	F25B 30/	H02S	
C10B 53/	C23C 14/16	F26B 3/		
C10G	C23C 14/18	F27D 17/		
C10J	C23C 14/20	F28D 17/		
C10L 1/	C23C 16/24	F28D 18/		
C10L 3/	C30B 29/06	F28D 19/		
C10L 5/	D21C 11/	F28D 20/		
C10L 9/	D21F 5/20	G02B 7/183		
C11C 3/10	E02B 9/	G05F 1/67		
C12N 1/13	E04D 13/	H01G 9/20		
C12N 1/15	E04H 12/	H01L 25/		
C12N 1/21	F01K	H01L 27/142		
C12N 15/	F01N 5/	H01L 27/30		
C12N 5/10	F02C 1/05	H01L 31/02		
C12N 5/12	F02C 1/06	H01L 31/03		
C12N 5/14	F02C 3/28	H01L 31/04		
C12N 5/16	F02G 5/	H01L 31/05		
C12N 5/18	F03B	H01L 31/06		
C12N 5/20	F03C	H01L 31/07		
C12N 5/22	F03D	H01L 51/42		
C12N 5/24	F03G 4/	H01L 51/43		
C12N 5/26	F03G 5/	H01L 51/44		
C12N 5/28	F03G 6/	H01L 51/45		
C12N 9/24	F03G 6/	H01L 51/46		
C12N 9/26	F03G 7/04	H01L 51/47		
C12N 9/28	F03G 7/05	H01L 51/48		
C12N 9/30	F21L 4/	H01M 12/		

List 2: Energy efficiency

IPC	IPC	CPC
B60K 6/10	E04F 13/12	Y02E 40/
B60K 6/28	E04F 13/14	Y02B 20/
B60K 6/30	E04F 13/15	Y02B 30/
B60L 3/	E04F 13/16	Y02B 40/
B60L 50/30	E04F 13/18	Y02B 50/
B60W 10/26	E04F 15/18	Y02B 60/
C09K 5/	E04F 15/20	Y02B 70/
E04B 1/62	E06B 3/263	Y02B 80/
E04B 1/64	E06B 3/267	Y02B 90/
E04B 1/66	E06B 3/273	Y02E 60/
E04B 1/68	E06B 3/277	Y02E 70/
E04B 1/70	F03G 7/08	Y02P 10/25
E04B 1/72	F21K 99/	Y02P 10/26
E04B 1/74	F21L 4/02	Y02P 10/27
E04B 1/76	F24H 7/	Y02P 10/28
E04B 1/78	F28D 20/	Y02P 10/29
E04B 1/80	G01R	Y02P 20/121
E04B 1/82	H01G 11/	Y02P 20/122
E04B 1/84	H01L 33/	Y02P 20/123
E04B 1/86	H01L 51/5	Y02P 20/124
E04B 1/88	H01M 10/44	Y02P 20/125
E04B 1/90	H01M 10/46	Y02P 20/126
E04B 1/92	H02J	Y02P 20/127
E04B 1/94	H05B 33/	Y02P 20/129
E04B 1/98		Y02P 20/131
E04B 2/		Y02P 20/132
E04B 5/		Y02P 40/121
E04B 7/		Y02P 40/123
E04B 9/		Y02P 60/14
E04C 1/40		Y02P 60/15
E04C 1/41		Y02P 70/143
E04C 2/284		Y02P 70/145
E04C 2/288		Y02P 70/163
E04C 2/292		Y02P 70/24
E04C 2/296		Y02P 70/261
E04D 1/28		Y02P 70/263
E04D 13/16		Y02P 70/623
E04D 3/35		Y02P 70/635
E04F 13/08		Y02P 70/639
E04F 13/09		Y02P 70/647
E04F 13/10		Y02P 80/1

List 3: Recycling and Reuse

IPC	IPC	CPC
A43B 1/12	C21B 3/08	Y02E 50/3
A43B 21/14	C21B 3/10	Y02P 10/21
B03B 9/06	C22B 19/28	Y02P 10/22
B22F 8/	C22B 19/30	Y02P 10/23
B29B 17/	C22B 25/06	Y02P 10/24
B29B 7/66	C22B 7/	Y02P 20/147
B30B 9/32	C25C 1/	Y02P 20/148
B62D 67/	D01F 13/	Y02P 20/149
B65D 65/46	D01G 11/	Y02P 20/58
B65H 73/	D21B 1/08	Y02P 60/87
C03B 1/02	D21B 1/10	Y02P 70/179
C03C 6/02	D21B 1/32	Y02P 70/24
C03C 6/08	D21C 5/02	Y02P 70/263
C04B 11/26	D21H 17/01	Y02P 70/267
C04B 18/04	H01B 15/	Y02P 70/279
C04B 18/06	H01J 9/50	Y02P 70/625
C04B 18/08	H01J 9/52	Y02P 70/627
C04B 18/10	H01M 10/54	Y02P 70/629
C04B 18/12	H01M 6/52	Y02P 70/633
C04B 18/14		Y02P 70/649
C04B 18/16		Y02P 70/651
C04B 18/18		Y02P 70/653
C04B 18/20		Y02P 80/40
C04B 18/22		Y02W 30/5
C04B 18/24		Y02W 30/6
C04B 18/26		Y02W 30/7
C04B 18/28		Y02W 30/8
C04B 18/30		Y02W 30/9
C04B 33/132		Y02W 90/2
C04B 33/135		
C04B 33/138		
C04B 7/24		
C04B 7/26		
C04B 7/28		
C04B 7/30		
C05F		
C08J 11/		
C09K 11/01		
C10G 1/10		
C10L 5/46		
C10L 5/48		
C10M 175/		
C11B 11/		
C11B 13/		
C14C 3/32		
C21B 3/04		
C21B 3/06		

List 4: Transportation

List 5: Production or Processing of Goods

IPC	IPC	CPC	CPC
B60K 16/	F16H 48/14	Y02T	Y02P
B60K 6/	F16H 48/16		
B60L 11/18	F16H 48/18		
B60L 7/10	F16H 48/19		
B60L 7/12	F16H 48/20		
B60L 7/14	F16H 48/22		
B60L 7/16	F16H 48/24		
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B60W 20/	H02J 7/		
B61	H02K 29/08		
B62D 35/	H02K 49/10		
B62K			
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B63B 1/34			
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B63H 9/			
B64G 1/44			
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F16H 48/08			
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Chapter 5

Natural Resources and Technology - on the Mitigating Effect of Green Tech

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Abstract

This paper deals with the question as to whether technology can lessen the problem of scarce resources. Focusing on fossil and biomass materials as important resources for production and consumption, the paper empirically investigates whether environmental innovations reduce the material usage in European economies. A dynamic panel model is employed to estimate the effect of environmental innovations on the use of fossil and biomass materials. It shows that there is no continuously mitigating effect of green technology. For biomass, no significant technology effects are found. Fossil materials are saved by innovations in recycling as well as by new production and processing technologies, but not by all categories of relevant green technology.

Keywords: Dynamic Panel ® Environmental Innovation ® Material Flows ® Patent Data ® Social Metabolism ® Sustainable Development

JEL Classification: Q01; Q55; Q56; Q58

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5.1 Introduction

The onset of the industrial revolution and the utilization of fossil fuels marked a shift in the human-environment interaction (Fischer-Kowalski, 2011; Fischer-Kowalski et al., 2014; Haberl et al., 2011). Drastic increases in environmental pressures have led researchers to label our current era as ‘Anthropocene’, indicating that humanity has become a major force in influencing natural processes on planet earth (Steffen et al., 2007). Human activity and its effects on the earth system carry the risk of abrupt global environmental change (Rockström et al., 2009). Researchers have proposed indicators of Economy Wide Material Flow Accounting (EW-MFA) to capture the utilization of natural resources by humans, given the interconnectedness of material usage with holistic environmental effects (Agnolucci et al., 2017; Behrens, 2016; Fischer-Kowalski et al., 2011; Weisz et al., 2006). Within the past four decades (1970-2010) material extraction has tripled on a global scale, from roughly 22 billion to 70 billion tons (UNEP, 2016).

The concept of ‘social metabolism’ refers to the interrelation of human societies with both their natural environment and other societies. It encompasses flows of materials and energy as well as related processes that are controlled by humans for the purpose of reproducing and evolving their society (Pauliuk and Hertwich, 2015). Historically, three broad ‘socio-metabolic regimes’ have been distinguished, namely the hunter-gatherer regime, the agrarian regime, and the industrial regime (Fischer-Kowalski et al., 2014; Haberl et al., 2011). The notion of ‘socio-metabolic regime’ has been established to distinguish fundamentally different socio-metabolic profiles, which can be characterized by the energy system a society depends upon, including conversion technologies and energy sources, land and material use, as well as related indicators such as population density (Fischer-Kowalski, 2011; Haberl et al., 2011). These socio-metabolic profiles are directly related to the composition of material usage, such as the shares of biomass, fossil fuels, metal ores, and non-metallic minerals. These reflect the relevance of specific materials as inputs to society. The neolithic revolution, i.e. the shift to an agrarian regime, was associated with the active utilization of solar energy, the conversion of land for agriculture, the domestication of animals, and other changes leading to increases in energy and material use (Fischer-Kowalski et al., 2014; Haberl et al., 2011). The industrial revolution, i.e. the shift to a ‘fossil energy system’, led to strong increases in energy and material use, population density, and trends such as urbanization (Fischer-Kowalski et al., 2014; Haberl et al., 2011). Given the strong environmental implications of a fossil-based energy system at the current scale - with forecasts considering even larger scales (Haberl et al., 2011) and doubts on the longevity of a fossil-based system (Lipson, 2011; Murphy and Hall, 2011; Shafiee and Topal, 2009; Turner, 2008) - another fundamental shift in the socio-metabolic regime is needed today (Fischer-Kowalski, 2011; Haberl et al., 2011).

Both fundamental shifts as well as gradual changes in the social metabolism are driven by and associated with technological changes. The shift to the agrarian regime was based upon new technologies, allowing the conversion of land, mining for metals and domesticating animals. Fundamentally, technology facilitated the utilization of new sources of energy and labor (Cordes, 2009). The shift to the industrial-regime was based on building capabilities to use fossil fuels. Changes within socio-metabolic regimes are also associated with technological change. While the breakthrough of coal usage was associated with the steam engine and railroads, the utilization of petroleum was associated with automobiles and the industrialization of agriculture (Fischer-Kowalski, 2011). Hence, technology can be considered as having facilitated, instead of reduced, environmental pressures by enabling the shift to fossil fuels as energy sources instead of biomass (Fischer-Kowalski et al., 2014; Haberl et al., 2011). Despite this historical role of technology and new technology, which lead to rebound effects, economic growth and uncertain environmental effects (Aghion and Howitt, 1998; Binswanger, 2001; Hepburn et al., 2018), it remains inevitable that innovations are sought for, to facilitate technological change that allows the highest possible prosperity without transgressing environmental boundaries (Barbieri et al., 2016; Canas et al., 2003; Haberl et al., 2011; Popp et al., 2010; UNEP, 2016, 2011). More specifically, certain technologies are considered to be more advantageous for the environment and are consequently pursued with high priority (European Commission, 2011a). In this vein, so-called ‘directed technical change’ aims at the utilization of specific environmentally beneficial technologies (Acemoglu et al., 2012; Aghion et al., 2016; Hepburn et al., 2018).

The European Union (EU) has developed multiple programs and initiatives, setting ambitious targets for improvements in environmental productivity. Many of these initiatives put improvements in resource efficiency at the heart of EU environmental policy in order to secure prosperity and competitiveness, while causing less harm to the environment (European Commission, 2015, 2011b, 2010, 2008). Among the necessary measures are changes in the energy supply structure as well as efficiency improvements in production (European Commission, 2019). The shift to green technologies is considered a necessity in order to achieve the ambitious environmental and economic goals. This is reflected in the ‘EU Eco-innovation Action Plan’ (EcoAP) (European Commission, 2011a), which constitutes an important element of the European policy for sustainable consumption and production. Hence, we will focus on the EU-27 countries,[88] given their institutional commonalities due to the shared EU framework including the strong emphasis on green technologies as a means to confront climate change and resource scarcity.

In this paper we focus on the resource saving effects of green technologies on the biomass and fossil fuels material groups. Historically, it has been the shift from biomass to a fossil-based energy system that has facilitated unprecedented population and economic growth (Fischer-Kowalski, 2011; Fischer-Kowalski et al., 2014; Haberl et al., 2011). Biomass was the dominant material group for human use, before its relevance declined strongly within industrial societies (Fischer-Kowalski et al., 2014; Haberl et al., 2011; Krausmann et al., 2009). Fossil fuels were an irrelevant material group within the agrarian regime, but are a key ingredient to the material-use profile of industrial countries (Fischer-Kowalski et al., 2014; Haberl et al., 2011; Schaffartzik et al., 2016). Further, these material groups build the foundation for modern societies as they are irreplaceable in terms of providing nutrition and energy (Haberl et al., 2011; Schramski et al., 2015; Weisz et al., 2006). There are doubts regarding the potential of alternative energy sources to enable similar societal organization (Haberl et al., 2011). Moreover, both materials are likely limited in their scope for endeavors towards a circular economy (Haas et al., 2015). While fossil fuels are essentially non-renewable and thus represent a final consumption of environmental value by humans, unsustainable reductions of living biomass are directly related with survival threats to the human species (Schramski et al., 2015). From a historical perspective, it has recently been suggested that the shift to fossil fuels be reversed (Fischer-Kowalski, 2011; Haberl et al., 2011). Shifts to economic structures based on biomass and biological processes are being considered (Ingrao et al., 2016), as biomass use is viewed as being more sustainable (Gustavsson et al., 1995). Both biomass and fossil fuel usage are directly related to multiple environmental problems, such as land-use change and emissions (Behrens, 2016). Further, given negative developments in energy returns on investments, the reduction of their use is a key concern for reductions of environmental pressure (Behrens, 2016).

Consequently, in this paper we will aim at disentangling the effects of green technologies on the biomass and fossil fuel usage in European economies. The paper is structured as follows: section two will provide an overview on the existing research on the environmental effects of green technologies, as well as more detailed explanations on biomass and fossil fuels. Section three introduces the data employed. Section four explains the method used in our analysis.

[88] Croatia is not included in our sample for reasons explained in the methodical part.

Section five provides our empirical results, which are then discussed and concluded in section six.

5.2 Literature Review

This paper draws upon the literature on the environmental effects of Environmental Innovation (EI),[89] as well as on the literature concerning backgrounds of biomass and fossil fuels. It is necessary to address the increase of material productivity, and thus the reduction of material use, in international de-carbonization strategies (Behrens, 2016). There is a physical relationship between the quantity of raw materials used in industrial processes, the amount of energy that is required, and greenhouse gas emissions, since the latter are emitted during all stages of product life cycles (Behrens, 2016).

A directed technological change capable of reducing the material consumption does, thus, play a key role in reaching environmental goals. The concept of technological change is widely discussed in the literature as a means to achieve the aim of sustainable economic growth (Acemoglu, 2002; Acemoglu et al., 2012; Jaffe et al., 2002; Popp et al., 2011, 2010), as environmental problems are not adequately addressable with current technologies (Popp et al., 2010). Empirical studies investigating the environmental effects of EI focus on emissions (Carrión-Flores and Innes, 2010; Costantini et al., 2017; Ghisetti and Quatraro, 2017; Wang et al., 2012; Weina et al., 2016; Zhang et al., 2017) or energy intensity (Wurlod and Noailly, 2016). However, it is evident that economic activity is accompanied by various environmental pressures. Material-use indicators have been considered appropriate to assess integrated environmental problems (Agnolucci et al., 2017; Behrens, 2016; Fischer-Kowalski et al., 2011). It is still up to empirical studies to investigate the concrete effects of green technologies on material use. This is what this paper will contribute to.

Besides the threats posed by climate change - that have become a major stimulus for renewable energy sources (McKendry, 2002) - growing external energy dependency and diminishing fossil fuel reserves are recognized as the most relevant and worrying issue in the energy sector (Carneiro and Ferreira, 2012). Biomass is seen as a source of energy, which is indigenous and available in most countries (McKendry, 2002). Contrary to fossil fuels, it is considered that CO_2 purely released by the conversion of new biomass does not contribute CO_2 to the atmosphere (Behrens, 2016). However, this does not consider the emissions released in agriculture or

[89] The term environmental innovation is used interchangeably throughout this paper with the overall concept of green technologies.

forestry by the usage of fossil-fuel-based machineries, or potential land-use changes, affecting e.g. terrestrial sinks (Behrens, 2016). Nevertheless, when produced by sustainable means,[90] CO_2 released by the conversion of biomass is approximately the same amount that is captured and stored during its growth phase. Furthermore, biomass production, when applied in a less intensive way, includes other ecological and environmental benefits. This includes the reduced need for fertilizers and pesticides, the potential to restore degraded land, and potential increases in biodiversity compared to current agricultural practice (McKendry, 2002).

Technological development, relating to the production and conversion of biomass, increasingly promises the application of biomass as a fuel at lower costs and higher conversion efficiency (McKendry, 2002). The potential overall effects that technology could exert on the consumption of biomass are both diverse and divergent. Improvements in small- and micro-scale biomass-fueled 'combined heat and power (CHP)' systems, for example, comprise a massive market potential worldwide (Dong et al., 2009). A large-scale application would thus lead to increased biomass consumption. In briquetting or gasification technologies, potential efficiency effects could be utilized for reductions in consumption. However, those efficiency gains could just as well accelerate the shift towards biomass, increasing consumption. The same holds true for developments in harvesting technologies. By increasing cost effectiveness, improvements could lead to a commercialization of formerly less attractive materials, like microalgal biomass (Wan et al., 2015) for fuel and energy production (Pragya et al., 2013). Improvements in recycling technologies are likely to reduce the consumption of biomass, at least in terms of raw material consumption concerning paper, for example (Haas et al., 2015). Improvements in waste-to-energy technology, among others, can reduce the new biomass required for energy generation, since municipal solid waste increasingly becomes an input factor (Matsakas et al., 2017; Pham et al., 2015). These examples demonstrate the complex, potentially diverging dynamics for biomass. Therefore, there is not one clear and unidirectional effect that can be expected.

Fossil fuels are fossilized biomass, taking millions of years to be converted into fossils like coal and oil (McKendry, 2002). The renunciation of these fuels and a massive reduction in their consumption is considered a key strategy to confront environmental degradation. Nevertheless, fossil fuels still constitute over 80% of the global primary energy mix (Behrens, 2016).[91] Fossil fuels are combusted in an irreversible manner (Haas et al., 2015), and the CO_2 released cannot be captured by the same source in an adequate time horizon (McKendry, 2002). Besides the

[90] In terms of CO_2 this would mean without the usage of fossil-fuel-based machines, and without an impact on e.g. terrestrial sinks by land-use changes.
[91] In 2013.

usage of fossils as material input for products such as plastics, generally the main potential for the reduction of fossil fuel consumption lies within energy related technologies. Renewable energy technologies, like solar, wind, or geothermal power plants have the potential to reduce material consumption, as they are less material intensive than fossil-fuel-based ones in terms of material input per unit of energy output (Raugei et al., 2012). Therefore, they could reduce the fossil-based primary energy input (Haas et al., 2015). This has the potential to significantly save the remaining stocks of fossil fuels (Raugei et al., 2012). Furthermore, all technological developments increasing energy efficiency reduce the need for fossil fuels.[92] Recycling technologies exert an effect on fossil fuel usage due to plastics and other materials that contain fossils, such as bitumen and lubricants (Haas et al., 2015). Intuitively, EI has the potential to reduce fossil fuel and biomass consumption, as well as environmental pressure in general. In the following sections of this paper we will evaluate the effect of environmental innovation on biomass and fossil usage in Europe.

5.3 Data

We constructed a panel dataset for the EU-27 countries between 1990 and 2012. This time frame was chosen to make all variables compatible to the material use data, which offers time-series starting from 1990.[93] To analyze the effects of environmental innovation (EI) on material usage, we decided to focus on material input. Material input indicators can be derived from the EW-MFA methodology and account for all materials that enter the socio-economic system of a country (Bringezu et al., 2004; Fischer-Kowalski et al., 2011). Material input is calculated by summing up domestic extraction, i.e. materials extracted in the country itself, and material imports (Im), i.e. materials entering the economy by being imported from abroad. Consumption indicators, i.e. material input minus exports, in our view perform worse than input indicators in capturing the material dependency of an economy to satisfy its production and consumption. Especially in light of analyzing technology effects, important information would be lost if reduced material inputs for exported goods were not accounted for.

Two different material input indicators can be constructed. Direct Material Input (DMI) is constructed by adding import flows to domestic extraction, with imports being measured by their actual weight when crossing the border (UNEP, 2016). Raw Material Input (RMI) accounts for upstream flows of imported commodities by assigning these as Raw Material

[92] Ceteris paribus.
[93] Concerning the indicator Raw Material Input (RMI).

Equivalents (RME_{Im}) (UNEP, 2016). These RME_{Im} can be calculated by applying multiregional input-output-models (Wiedmann et al., 2015). Both indicators have merits and drawbacks that are inherent in their calculation. RMI introduces some uncertainties due to the application of input-output-models (Eisenmenger et al., 2016) as well as potential sensitivity to changes in foreign technology and production, which influence the accounted upstream flows. On the contrary, DMI directly reflects the mass of materials actually processed in the economy. However, a major issue of DMI is that the offshoring of material intensive production steps is not accounted for (Schaffartzik et al., 2016). This can obscure results if reductions of material usage are mainly due to offshoring (Wiedmann et al., 2015), while the global reducing effect of reducing imports may also not be fully accounted for. Hence, given the focus of our study, we consider RMI as the more suitable indicator, and will base our main analysis on RMI. Nonetheless, we also conducted the analysis for DMI and will compare the resulting differences between the two indicators.

We obtain data on material flows from the Global Material Flows Database, provided by the United Nations Environment Programme (UNEP) (UNEP, 2016). The dataset is available at http://www.resourcepanel.org/global-material-flows-database. As mentioned above, the time-series for Raw Material Equivalents ranges from to 1990 to 2012.[94] We extract data on domestic extraction and imports and calculate RMI by adding RME_{Im} to domestic extraction, while adding regular import data in the construction of DMI. We construct the indicators this way, both for biomass and fossil fuels. If either domestic extraction or import data is missing we set our material input variable to missing. Within the period of 1990 to 2012 the same observations are missing for RMI and DMI for both material classes.

Given our interest in analyzing the effects of green technologies on material usage we utilize patent data on environmental innovation (EI). We construct patent stocks as a measure of installed and available technological capabilities (Costantini et al., 2017; Popp et al., 2011). Following Popp et al. (2011) the patent stock is constructed according to the following formula:

$$(1)\ K_{i,t} = \sum_{s=0}^{\infty} e^{-ß_1(s)}\left(1 - e^{-ß_2(s+1)}\right) PAT_{i,t-s}$$

$ß_1$ is the knowledge depreciation rate, accounting for the decreasing relevance of technologies over time (Weina et al., 2016). $ß_2$ is the diffusion rate, accounting for the time technologies need to spread (Weina et al., 2016). Due to multiplying the rate of diffusion with $s + 1$,

[94] Data after 2012 is available, however according to the Technical Annex should not be used for statistical analysis.

diffusion is not constrained to zero in the current period (Popp et al., 2011). In line with previous work, we set the knowledge depreciation rate to 0.1, and the diffusion rate to 0.25 (Popp et al., 2011; Weina et al., 2016).

The use of patent data is accompanied by drawbacks that have been extensively discussed in the literature (Haščič and Migotto, 2015; Johnstone et al., 2010; Lanjouw and Mody, 1996; Popp et al., 2011; Weina et al., 2016). Nonetheless, patent data is considered the most suited indicator for innovation as it measures intermediate output, is quantitative, widely available and provides detailed information due to the technology classes assigned (Dernis and Khan, 2004; Griliches, 1990; Haščič and Migotto, 2015).

In order to avoid potential drawbacks of patent data we generated the patent data under the following conditions. We rely on multinational patent applications at the European Patent Office (EPO), thus avoiding issues concerning patent quality and comparability (Johnstone et al., 2010). To further increase patent quality and avoid double counts, we count only the first EPO patent within a patent family. Given our focus on the utilization of an invention, we assign patents based on applicant data (Ghisetti and Quatraro, 2017), counting the patent applications at which an applicant from a country participated. In order to capture the innovative effort undertaken in a timely manner, we utilize patent applications instead of granted patents (Costantini et al., 2017) and avoid regulatory delays when reflecting the timing of discovery by using the earliest filing year (Carrión-Flores and Innes, 2010; Costantini et al., 2017; Wang et al., 2012; Wurlod and Noailly, 2016). The patent data was retrieved from PATSTAT 2017b.[95]

To distinguish EI from other innovations, we utilize the technological classes of patent applications. The WIPO Green Inventory (GI) (Albino et al., 2014; Ghisetti and Quatraro, 2017; Kruse and Wetzel, 2014) and the OECD EnvTech indicators (EnvTech) (Costantini et al., 2017; Ghisetti and Quatraro, 2017; Haščič and Migotto, 2015) have been made available to make such discrimination feasible. However, given the heterogeneity of technologies included in these lists we defined several subdomains of EI, capturing potentially specific technological effects and dynamics. We construct a comprehensive EI variable by using all technological classes encompassed by the GI and/or the EnvTech (EI_Full). Further, we define innovation in the area of alternative energy production (EI_AEP) and green technologies relating to transportation (EI_Transp), since achieving the decarbonization of mobility and energy provision is considered crucial to achieve environmental goals. Further, we define EI in the area of recycling and reuse (EI_Recy), which fundamentally relates to concepts of resource efficiency and

[95] The b refers to the autumn version.

circular economy (European Commission, 2015; Haas et al., 2015). Beyond that we define EI in relation to energy efficiency (EI_EnEff), given the crucial importance of improved energy efficiency to reduce fossil usage. Further, we operationalize climate change mitigation technologies in the production or processing of goods (EI_ProGo), given the resource intensity of manufacturing. To ensure that the effects found for a subdomain of EI are not due to mistakes in choosing the EI boundary, we also construct a variable capturing all innovations (Total Innovation). If effects are found for an EI subdomain, but not for overall innovation, this robustness check ensures that we have isolated an actual effect of the specific EI technologies (Lanjouw and Mody, 1996; Wurlod and Noailly, 2016). A detailed list of technology classes constituting the five EI subdomains is provided in the Appendix (A8).

Further data is taken from the Cambridge Econometrics European Regional Database (ERD) and the World Bank World Development Indicators (WDI) database. Data on GDP and the sectoral share of the agricultural sector have been taken from the ERD. Data on energy structure, namely the share of fossil energy out of total energy, and data on net energy imports was taken from the WDI database. Descriptive statistics on all variables can be found in the Appendix (A1).

5.3.1 Development of Material Inputs Over Time

We will now explore the material inputs of biomass and fossil fuels using the RMI indicator. We will start by shortly discussing the size relation of biomass and fossil fuel usage. Then we discuss the dynamics over time of both material groups. Lastly, we will explore the composition of biomass and fossil fuels, given that these are constructed of disaggregated material groups.

Across our sample, biomass is quantitatively larger than fossil fuels. Biomass accounts on average for 1.26 times as much mass as fossil fuels. However, this relation diverges strongly (Min.: 0.29 ; Max.: 4.56). The relative significance of the two classes differs largely across countries. The highest average is found for Latvia with Biomass being 3.05 times as high as fossil fuels. The lowest average occurs in Slovakia, where biomass usage is only 0.46 times that of fossil usage. Fig. 1 shows the dynamics of biomass and fossil RMI alongside GDP for all 27 countries for the period 1993 to 2011. As can be seen, the proportions of biomass and fossils vary over time. While there is some growth in material inputs over time, it is evident that GDP growth is more pronounced. This indicates increased material efficiency. Comparing the first and last year (1993 and 2011), GDP is 1.43 times its initial value, while biomass is 1.29 times and fossils 1.11 times as large. This indicates that material efficiency improved more strongly for fossil materials than for biomass.

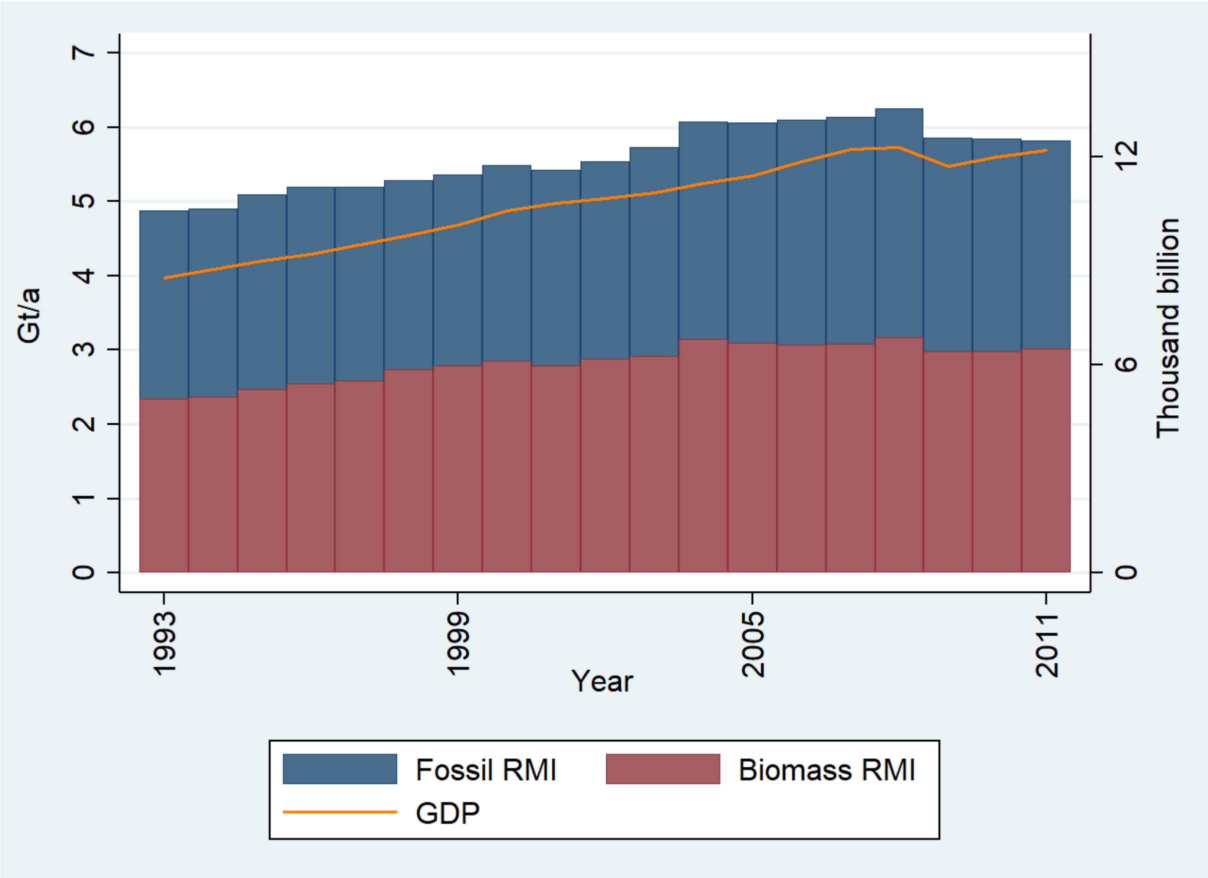

Figure 1: RMI and GDP in the EU-27 per year

Notes to Figure 1: *On the left-hand side RMI data (bars) is scaled as gigatons (1.000.000.000 tons) per year. On the right-hand side GDP data (line) is scaled in thousand billion per year. The graph covers the period 1993 to 2011, as all countries contributed data for these years.*[96]

Across the whole sample biomass grows by 2.08% on average. These dynamics are much stronger for fossil fuels with 4.53% average growth. These strong dynamics however occur primarily in the early 90s, due to structural dynamics which are discussed later. When excluding the years before 1996 from the calculations, average growth of fossils decreases to 1.85%. These changes are much less pronounced for biomass, where average growth decreases to 1.74%. For both material groups growth dynamics are more pronounced for RMI than for DMI.[97]

[96] For Fossil RMI the following countries and years are missing: Cyprus (2012), Czech Republic (1990-1992), Germany (1990), Estonia (1990-1991), Lithuania (1990-1991), Latvia (1990-1991), Malta (2012), Slovenia (1990-1991), Slovakia (1990-1992). Biomass RMI is missing for the same observations, except that data is given for Cyprus and Malta in 2012.

[97] For DMI the average growth rates have the following values. For the full sample (1990-2012): Biomass 1.33%, Fossil fuels 0.39%. For the reduced sample (1996-2012): Biomass 1.72%, Fossil fuels 0.64%.

Both biomass and fossil fuels are aggregated material groups consisting of subgroups with potentially diverging dynamics (Weisz et al., 2006). Biomass is aggregated from five subclasses that are available on an MF13 level,[98] namely crops, crop residues, grazed biomass and fodder crops, wood, and wild catch and harvest. Wood is considered to show different dynamics than agricultural biomass (Weisz et al., 2006). This could be particularly relevant given that we focus on material input indicators. Hence, we assessed the composition of Biomass DMI concerning potential underlying dynamics due to this distinction. Especially in Finland and Sweden wood is the most important biomass subgroup (>60%), followed by Estonia and Latvia (47%). Wood has the strongest changes in its biomass share in terms of magnitude. However, this corresponds to wood's general biomass share, which is the second highest behind crops. Crops are less volatile due to their subsistence character. In relative terms, the dynamics of wood usage are less pronounced than for wild catch and harvest, grazed biomass and fodder crops, and crop residues. Although the share of wood tends to increase over time, there are no clear patterns in these dynamics. Also, the strong volatility of the wood share seems to be in proportion to its overall relevance in the affected country. Hence, there are no compositional dynamics of biomass that seem relevant for our empirical analysis.

Fossil fuels are aggregated by summing up coal, petroleum, natural gas, and oil shale and tar sands. The composition plays a very important role, given that fossils mainly serve the same purpose as to provide energy (Haas et al., 2015). Yet, substantial differences between the subgroups occur as the calorific value of coal only amounts to 30-50% of the calorific value of oil and gas (Weisz et al., 2006).[99] Hence, we analyzed the fossil composition concerning the shares of coal compared to oil and gas. Oil shale and tar sands, according to the data, are not used by European countries. An exception is Estonia, which has high domestic extraction; ~85% of its fossil usage is accounted for by oil shale and tar sands. Therefore, Estonia was excluded from the calculation of the compositional dynamics. Strong substitutions of coal by oil or gas, and the other way around, could distort information. Such substitution would not be captured by energy structure variables[100] but implies different amounts of available energy, which are not reflected by the respective material inputs. Therefore, we calculated the share of coal in fossil DMI on the one hand, and the share of gas plus oil in fossil DMI on the other

[98] Material flow data disaggregated to 13 material classes, of which 5 are summed up to Biomass on MF-4 level, 4 are summed up to fossil fuels and each 2 to metal ores and non-metallic minerals.
Please note that data on Raw Material Equivalents (RME) is only available on an MF-4 level, which is why conducting the actual analysis on MF-13 level is not possible.
[99] Coal produces more CO_2 per unit of energy (Haberl et al., 2011).
[100] As all are still fossil energy carriers.

hand. Then, we looked at the changes of the gas plus oil share.[101] First, we clustered our time-series into four periods, from 1991-1995, 1996-2001, 2002-2007, and 2008-2012. It is striking that there seems to be a strong substitutional effect going on in the early 90s, as the average growth[102] is by far highest in the first period with 1.15 %, and then decreases each period to 0.68%, 0.26% and 0.04%. Hence, especially in the first years, coal was substituted by oil and gas. Likewise, in terms of absolute changes[103] the first period is most volatile with 2.53%, followed by 2.12%, 1.81%, and 1.59%. The highest average increase of oil and gas can be found in Luxembourg, Malta, Slovakia, Denmark, and Ireland. The highest volatility[104] occurs in Finland and Latvia. Although dynamics in substitution remain after 1995, this first period has by far the strongest dynamics and substitution towards oil and gas. The yearly dynamics of coal substitution and volatility are presented in Fig.2. Coal substitution is high and constant in the early 90s. An overall peak can be found in 1998, where both coal volatility and substitution exceed 3% on average. The volatility remains rather stable across the whole sample, being smaller in the second half of the sample. Substitution of coal is very pronounced in the early 90s, whereas it fluctuates around zero in the second half of the sample.

[101] We multiplied the change in the share by 100 to have the variable in %, e.g. a change from 0.01 to 0.02 implies 0.01*100 = 1% change.
[102] Given the definition of the variable, positive average growth directly implies that the share of oil and gas increased to the disadvantage of coal.
[103] Meaning that positive and negative change rates do not cancel out.
[104] Referring to absolute changes as explained in footnote before.

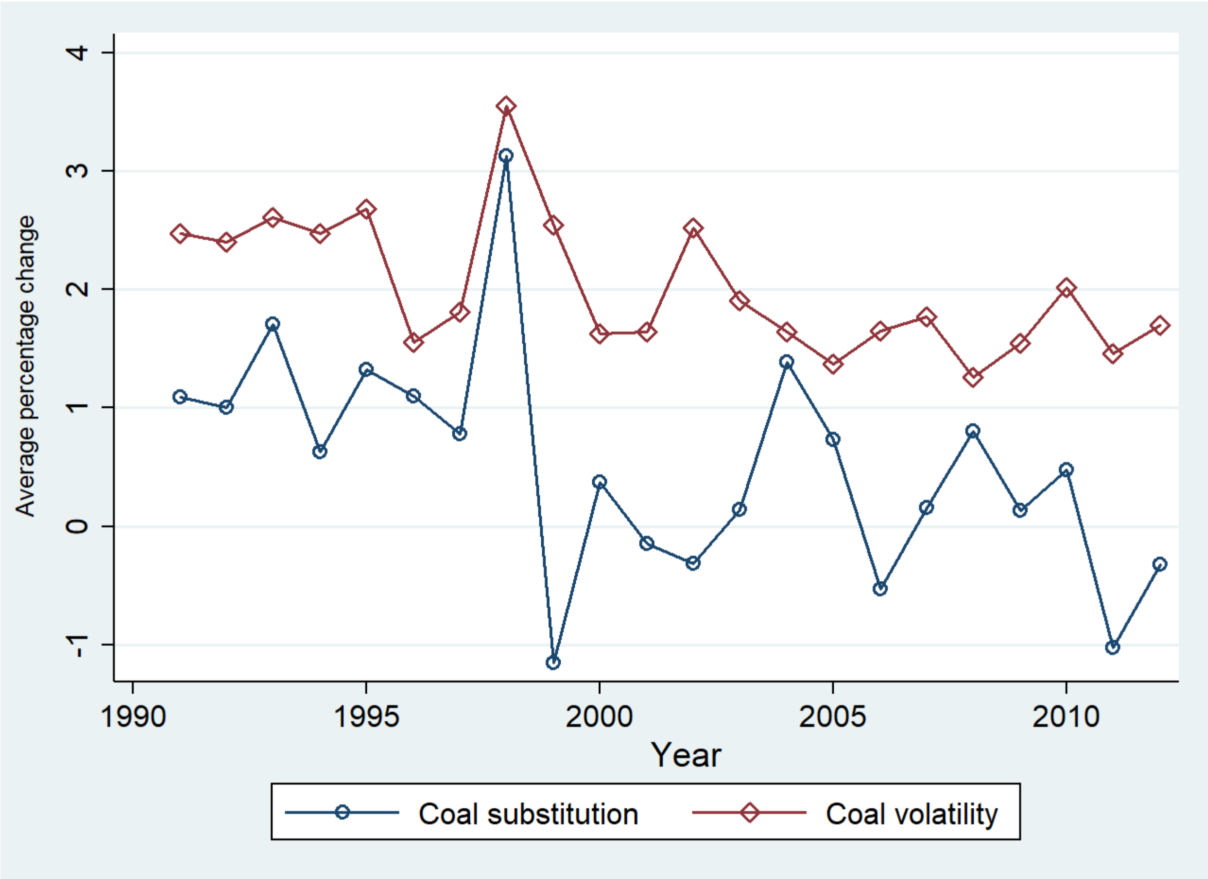

Figure 2: Yearly average changes within fossil DMI across European countries

Notes to Figure 2: *Coal Substitution refers to the average increase of the oil and gas share in fossil DMI. Coal volatility refers to the average changes of the oil and gas share in fossil DMI, regardless of the direction of change. Estonia was excluded from the calculations.*

5.3.2 Development of Environmental Innovation Over Time

We constructed five different areas of EI, besides the comprehensive definition (EI_Full). Among these categories' alternative energy production (EI_AEP) is the largest, followed by energy efficiency (EI_EnEff) and transportation (EI_Transp). Climate change mitigation in the production or processing of goods (EI_ProGo) follows, being larger than recycling and reuse (EI_Recy) as the narrowest domain according to the mean value (A1). Across the whole sample green innovation (EI_Full) is on average a fifth (19%) of overall innovation.[105] However, while this relative share is quite constant over time,[106] it varies across countries. The largest deviations of the relative role that green innovation (EI_Full) plays occur in smaller and less developed economies. The largest shares are found for Estonia and Slovakia with more than 30%, whereas

[105] The descriptive statistics are based on the stock measures of innovation.
[106] When clustering our sample in four time periods of 6 or 5 years the mean value varies between 18.4 and 19.9%. More volatile dynamics within a country are given.

Latvia has on average less than 10%. In general, the share of green innovation (EI_Full) is larger in the non-EU15[107] countries (22%) compared to the EU15 countries (18%).

When aggregating the data for the EU15 and non-EU15 countries, these shares of green innovation drop to 17 and 21% respectively. For both country groups, EI_AEP constitutes the largest EI domain, accounting for 37 (non-EU15) and 36% (EU15) of EI_Full. EI_EnEff accounts for roughly half as much, with 18% for non-EU15 and 19% for EU15 countries. EI_Transp constitutes a substantially larger share in the EU15 countries with 13%, compared to 10% in non-EU15 countries. A difference in the relative rank of EI domain exists for EI_ProGo and EI_Recy. In the EU15 countries, EI_Recy is the smallest domain accounting for 6% of green innovation, whereas EI_ProGo accounts for 8%. The opposite holds for non-EU15 countries where both domains account for ~9%, with EI_Recy being slightly larger.

The relevance of the EI domains varies over time. Fig. 3 shows the dynamics over time of the individual domains for non-EU15 countries. EI_AEP is excluded from the graph, to facilitate the visibility of dynamics going on in the other EI domains. The share of EI_AEP varies between 34 and 38%. The overall relevance of EI in general innovations is rather constant, ranging between 20 and 22%. EI_EnEff gains in relevance over time; a constant increase from 15% up to 23% can be found. EI_Recy experiences a similar development, starting at 7% and developing upwards to account for 12% of green innovation. EI_Transp and EI_ProGo remain rather stable, ranging from 9 to 12%, and 7 to 11% respectively. Their dynamics are opposed. While EI_Transp gains towards 2000 and loses relevance afterwards, EI_ProGo loses towards 2000 and regains afterwards.

[107] EU15 countries refer to the group of countries which joined the European Union before 2000. The non-EU15 countries, which joined the EU after 2000 are: Estonia, Latvia, Lithuania, Poland, Czech Republic, Slovenia, Slovakia, Hungary, Malta, Cyprus, Romania, and Bulgaria.

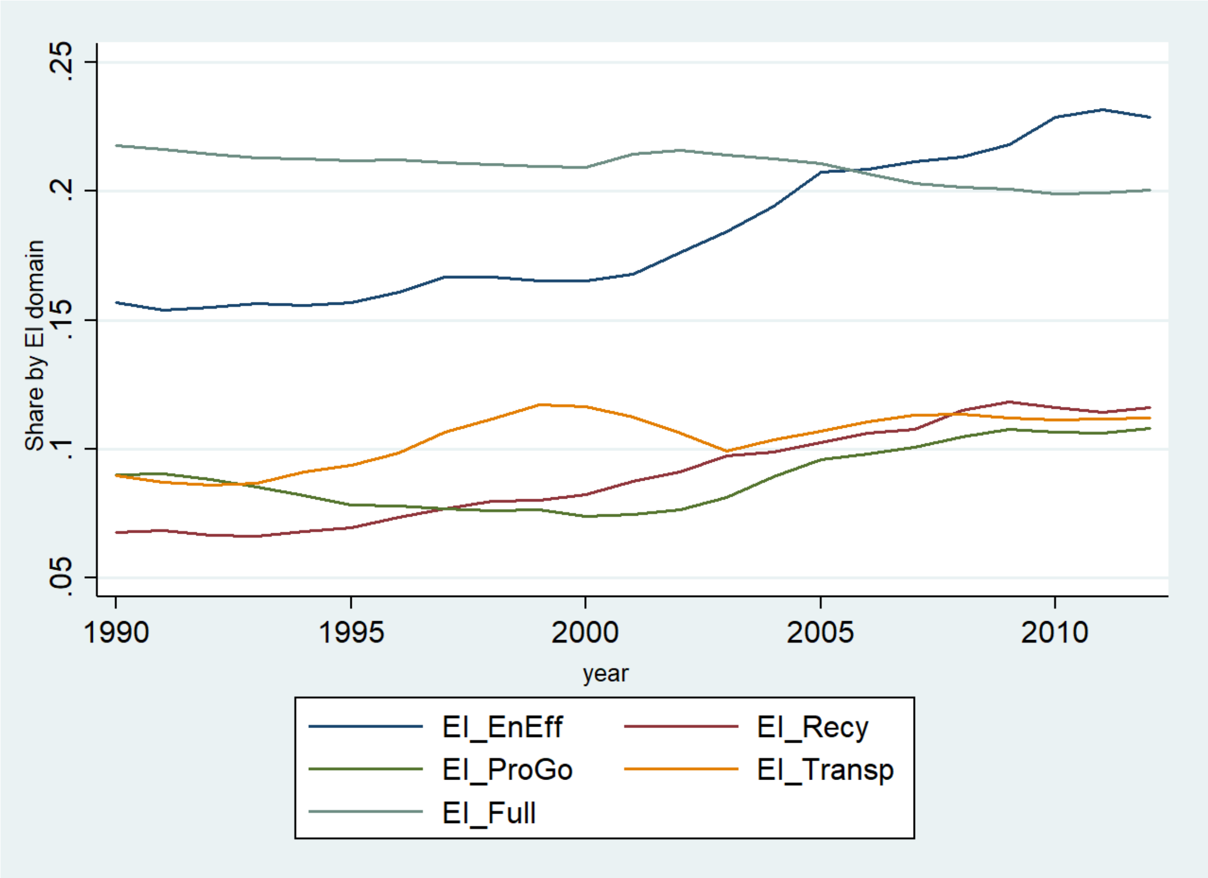

Figure 3: Development of EI domain shares in non-EU15 countries

***Notes to Figure 3**: The share of EI_Full is computed by dividing EI_Full by general innovation. All specific EI domain shares were computed by dividing by EI_Full. The stock values are aggregated for all countries of the group by year.*

Fig. 4 displays the corresponding data for the EU15 countries. As noted above, the share of green innovation is substantially lower, ranging between 17 and 18%. Again, EI_AEP is not displayed, since the share ranges between 35 and 40%. EI_EnEff again experiences a constant increase from 17 to 23%. EI_Transp shows very distinct relevance compared to the non-EU15 countries. Starting at 11% it experiences a constant increase as well, up to 16%. EI_ProGo remains fairly constant between 8 and 9% throughout our observation period. Like EI_Transp, EI_Recy shows dynamics diverging from the non-EU15 countries. It reaches its highest value at around 1995 with 7% but decreases afterwards to only 5% of green innovation.

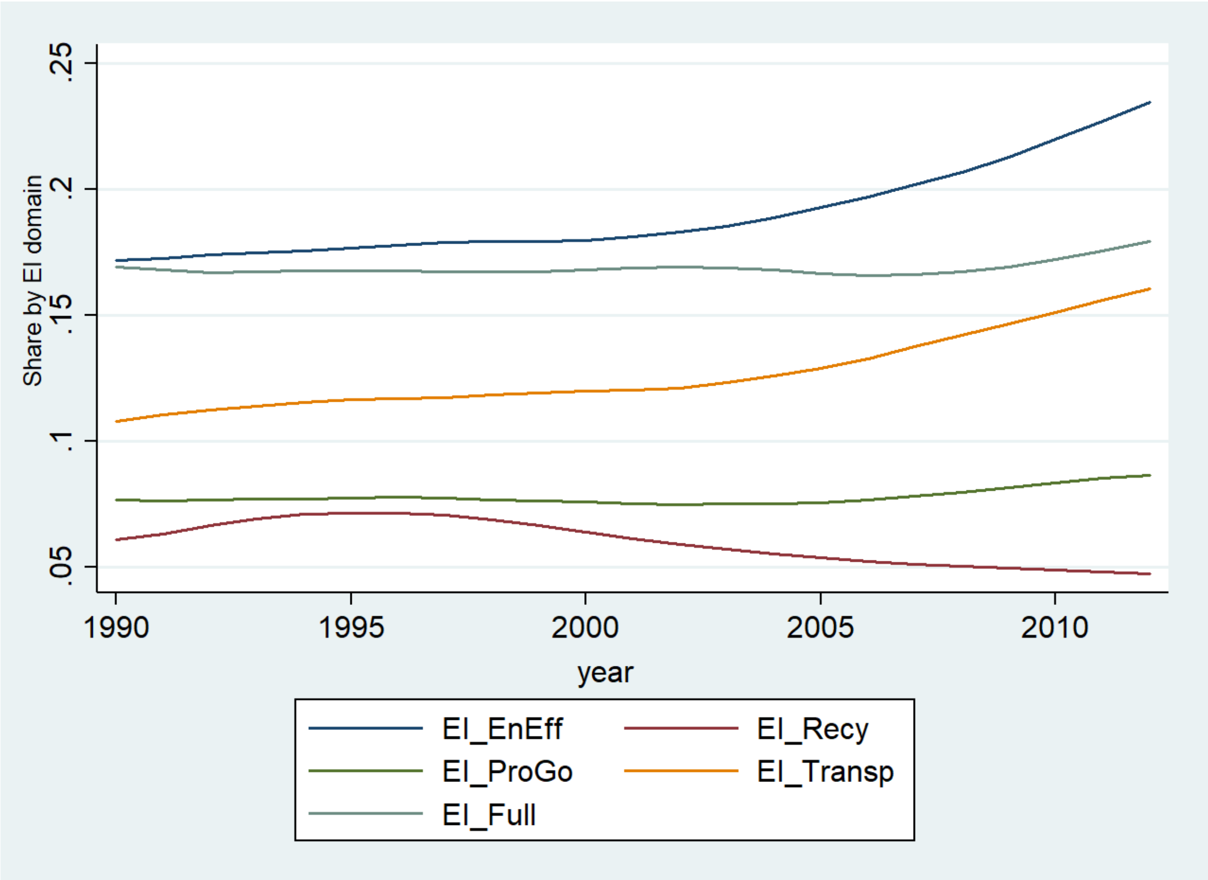

Figure 4: Development of EI domain shares in EU15 countries

Notes to Figure 4: *The share of EI_Full is computed by dividing EI_Full by general innovation. All specific EI domain shares were computed by dividing through EI_Full. The stock values are aggregated for all countries of the group by year.*

5.4 Method

A dynamic panel data approach is employed in this study, to incorporate the temporal dependency and dynamic existing between material flows and their own past values (Shao et al., 2017).

$$(2)\quad RMI_{i,t} = \sum_{j=1}^{J} \delta_j RMI_{i,t-j} + X'_{i,t}\beta + \mu_i + \psi_t + \varepsilon_{i,t}$$

$$with\ i = 1, \dots, N\ and\ t = 1, \dots, T$$

RMI_{t-j} represents the lagged dependent variable (LDV), X' is a $1\ x\ k$ vector of regressors, β denotes the $k\ x\ 1$ vector of coefficients, μ the country fixed effects, ψ the time fixed effects and

ε the error term. The subscript i denotes the cross-sectional unit (country) and t denotes the year.

Due to the given data structure - and to avoid the potentially biased estimates[108] and endogeneity problems - this study employs the one-step difference Generalized Method of Moments (GMM) estimator, an instrumental variable (IV) method. This method, proposed by Arellano and Bond (1991), is widely known as the Arellano-Bond estimator (AB). The usage of this estimator is in line with econometric literature since it outperforms other methods in long panels (Hwang and Sun, 2018; Judson and Owen, 1999).

The starting point of the AB estimator is given by first-differencing equation 2 above:

$$(3)\quad \Delta RMI_{i,t} = \sum_{j=1}^{J} \delta_j \Delta RMI_{i,t-j} + \Delta X'_{i,t}\beta + \Delta\psi_t + \Delta\varepsilon_{i,t}$$

This eliminates μ_i but causes that the LDV again is correlated with the error (Baltagi, 2008). This problem is encountered by the utilization of IV, in which the first-differenced variables are instrumented by their own lags. Those are highly correlated with the LDV, but not correlated with the error.[109] The basis and suggested advantage of the GMM procedure is the comprehension of the orthogonality conditions existing between y_{it} and ε_{it}, which are the imposed moment conditions:

$$(4)\quad E\left[RMI_{i,t-s}\Delta\varepsilon_{i,t}\right] = 0 \; and \; E\left[X_{i,t-s}\Delta\varepsilon_{i,t}\right] = 0$$

$$for\ t = j+2, \dots, T \; and \; s \geq j+1$$

The method requires that no second-order autocorrelation in the differenced equation is present, as this would render instruments invalid (Roodman, 2009) and lead to inconsistent estimates (Castro, 2013). On the contrary, first-order autocorrelation is uninformative (Roodman, 2009). Further, the exogeneity of the instruments is needed for consistency. Therefore, the Sargan specification test is used, in order to test for the validity of instruments (Castro, 2013; Roodman, 2009).

[108] Employing the well-known Fixed-Effects estimator (FE), aiming to eliminate the country fixed effects, leads to endogeneity problems caused by the presence of the LDV and thus to inconsistent estimates (Baltagi, 2008).
[109] These estimators allow the inclusion of endogenous, predetermined and exogenous regressors. Endogenous regressors are influenced by the contemporaneous error term, while predetermined regressors may be influenced by the error term in previous periods. In this manner, the strictly exogenous variables are instrumented by themselves and the endogenous or predetermined by their lagged levels (Castro, 2013).

The stationarity of variables was tested using unit root tests. According to the Fisher-test with drift, no variable is clearly non-stationary in levels (A2). However, we also conducted all stationarity tests for 1996 to 2012, where the fossil energy variable is non-stationary. Hence, we included fossil energy in first differences into the model, for both time periods.

5.5 Empirical Results

We now turn to the empirical estimations carried out. To secure the plausibility of our instrumentation choices and results, the AR2-test[110] and the Sargan test results support our modelling decisions.[111] We checked for soundness, specifically that the coefficient of the LDV lies either nearby or in-between the range of the estimated coefficient for fixed effects (downward biased) and OLS (upward biased) (Roodman, 2009). We do not report the results here, as there is no additional information gained. For each material group and indicator combination we chose a homogenous way of instrumentation to secure comparability. We treat the lagged dependent variable as predetermined and instrument it starting earliest with the second-lag of the non-lagged dependent variable (Roodman, 2009). For DMI we allowed more lags as instruments than for RMI, to secure sound estimations. Innovation and GDP are treated as endogenous (Agnolucci et al., 2017; Costantini et al., 2017). Further variables are treated as exogenous. We instrumented Innovation with the second to fourth lag.[112] GDP is instrumented with its second and third lag. AB estimations were conducted under orthogonal deviations transformation, instead of a first-difference transformation (Hayakawa, 2009; Hsiao and Zhou, 2017; Roodman, 2009).

5.5.1 Biomass

We now turn to our estimations concerning the usage of biomass. As indicated in section 3.1., we do focus on the overall sample. The results for all EI variables and Total Innovation can be found in Table 1. We considered our different EI classes in order to reflect potentially specific effects. Changes in the areas of EI_AEP and EI_Transp were considered to relate to the increasing importance of biomass materials for fuel usage and energy generation. Bioenergy is

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[110] Testing for second-order autocorrelation.

[111] Except for few cases, where however changing the instrumentation would not qualitatively influence the relevant results.

[112] Note that for Total Innovation and EI_Full, test results supported to go deeper. Hence, we used lags 3 to 5 for these two innovation variables only.

considered a potential field that may cause both the shift towards using biomass-based materials and additional material demand (Bird Life International, 2016). However, our results below show that none of these two groups exert a specific effect. Improvements in EI_EnEff could relate to reductions of used energy crops or fuel wood. Yet, energy efficiency also remained insignificant. The classes of which the most direct effect could have been expected are EI_Recy and EI_ProGo. These can be quite directly related to reductions of biomass needed for paper production, reusage of wood products, reduced energy need, and further aspects that have a potential to influence biomass usage (Haas et al., 2015). These categories also do not have a significant effect, which also holds for Total Innovation and EI_Full. We also tested specifications for DMI (A3) with the main results remaining unchanged.

Table 1: GMM results for RMI Biomass for all countries from 1990-2012

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model	AB	AB	AB	AB	AB	AB	AB
Dep. Var.	RMI Biomass	RMI Biomass	RMI Biomass	RMI Biomass	RMI Biomass	RMI Biomass	RMI Biomass
L1.RMI Biomass	0.477*	0.451	0.641**	0.565**	0.746***	0.682**	0.634*
	(0.251)	(0.303)	(0.254)	(0.220)	(0.218)	(0.252)	(0.309)
Total Innovation	-0.0451						
	(0.0330)						
EI_Full		-0.0331					
		(0.0292)					
EI_EnEff			-0.00681				
			(0.0186)				
EI_AEP				-0.0238			
				(0.0201)			
EI_Transp					-0.0313		
					(0.0271)		
EI_Recy						-0.0205	
						(0.0232)	
EI_Manu							-0.0246
							(0.0265)
GDP	0.713***	0.631**	0.654**	0.579***	0.564**	0.565*	0.792**
	(0.244)	(0.243)	(0.244)	(0.203)	(0.222)	(0.302)	(0.354)
Agricultural Intensity	3.475***	3.062***	3.363***	2.942***	2.998***	3.002***	3.954***
	(0.764)	(0.708)	(0.829)	(0.650)	(0.954)	(0.955)	(1.213)
Time-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	552	550	513	530	497	501	495
No. of Countries	27	27	27	27	27	27	27
No. Of Instruments	31	31	31	31	31	31	31
AR1-Test	-2.64	-2.53	-2.55	-2.64	-2.59	-2.75	-2.29
	[0.008]	[0.012]	[0.011]	[0.008]	[0.010]	[0.006]	[0.022]
AR2-Test	0.99	0.95	1.52	1.52	1.54	1.34	1.49
	[0.322]	[0.340]	[0.128]	[0.128]	[0.124]	[0.182]	[0.136]
Sargan-Test	12.74	12.25	10.22	5.13	11.31	1.76	6.40
	[0.047]	[0.057]	[0.116]	[0.528]	[0.079]	[0.940]	[0.380]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

We continue by briefly discussing the results concerning the other variables. The coefficient of the lagged dependent variable lies at ~0.6 and is significant across most specifications, supporting the usage of a dynamic model.

GDP is found to be significant with a coefficient ranging between 0.56 and 0.79, indicating that a 1% increase of GDP is associated with a 0.56 to 0.79% increase of biomass RMI. This result seems counterintuitive as biomass is usually considered a subsistence material, being mainly bound to population dynamics and not as much to economic development (Krausmann et al., 2009; Steinberger et al., 2010; Steinberger and Krausmann, 2011; Weisz et al., 2006). However, despite being a subsistence material, increases in affluence have been noted to change e.g. dietary patterns towards more animal products (Weinzettel et al., 2013; Wiedmann et al., 2015) that cause high material usage (Haas et al., 2015; Weisz et al., 2006).

The agricultural sector is highly significant and exerts an over-proportional effect on biomass RMI. A one percentage point increase in the value-added share of the agricultural sector is associated with a 3 to 4% increase of RMI. This is likely due to the high biomass intensity of agriculture, such as livestock (Weisz et al., 2006). The results seem to correspond to findings that higher shares of the agricultural sector are related to lower levels of material productivity (Fernández-Herrero and Duro, 2019; Gan et al., 2013).

As discussed in section three, we did not find relevant compositional dynamics of the biomass variable. Still, we conducted an analysis under the exclusion of countries, when analyzing those innovation variables which were somewhat close to significant results in the full sample.[113] The country groups that were taken into consideration were those which have a high share of wood (Finland and Sweden), countries with a very specialized composition - namely more than 60% share of the main biomass group on average - (Malta, Finland, Netherlands and Sweden), and countries with the highest volatility of the wood share (Estonia and Latvia, and additionally also Finland, Luxembourg, Sweden and Slovakia). Further, we excluded the year 1998, as in this year the strongest dynamics of wood and crops (5.39% respective 3%) were observed. However, none of these robustness checks had any influence on the results. Similarly, alternative instrumentation did not change the results in a relevant way.

[113] We tested those constellations were the p-value of Innovation was below 0.3.

5.5.2 Fossils

We continue with our results on fossil material usage. Given our findings in section 3.1., we decided to put our main focus on the time-frame 1996 to 2012, to avoid distortions by dynamics within our dependent variable. The growth dynamics of RMI were extremely high in the early 90s, coinciding with strong substitutional dynamics within the fossil variable, as coal was strongly substituted by oil and gas. We will discuss differences between the results for 1996-2012 and the full time-period in light of these observations. As an additional control on substitutional dynamics we included energy imports, to capture reductions of domestic coal in favor of oil and gas.

The results are displayed in Table 2. Total innovation and innovation in the areas of EI_Full,[114] EI_EnEff, EI_AEP and EI_Transp are found to exert no relevant effect on fossil usage. In the case of EI_AEP we also conducted the analysis under the exclusion of the fossil energy variable, which did not change the results. Yet, we do find that EI_Recy and EI_ProGo can be seen as significant in this sample. EI_Recy is significant at the 5% level with a coefficient of -0.024, indicating that a 1% increase is associated with a 0.024% reduction of fossil RMI. EI_ProGo is significant at the 10% level, with a coefficient of -0.0155. While both EI_Recy and EI_ProGo are insignificant in the full sample from 1990 to 2012 (A4), their coefficient sizes are of a similar magnitude, specifically -0.0164 for EI_Recy and -0.00757 for EI_ProGo. It should be noted that for DMI, all innovation variables remain insignificant in both samples (A5 and A6).

[114] Please note that under different instrumentation the Sargan test switches into the acceptable realm. Given that we wanted to present a consistent instrumentation across all EI groups we decided to report this specification, despite of the issues indicated by the Sargan test. However, the qualitative results are not different in sound specifications.

Table 2: GMM results for RMI Fossils for all countries from 1996-2012

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model Dep. Var.	AB RMI Fossils	AB RMI Fossils	AB RMI Fossils	AB RMI Fossils	AB RMI Fossils	AB RMI Fossils	AB RMI Fossils
L1. RMI Fossils	0.919***	0.856***	0.896***	0.912***	0.867***	0.825***	0.867***
	(0.0962)	(0.100)	(0.0765)	(0.112)	(0.0879)	(0.113)	(0.0871)
Total Innovation	0.000321						
	(0.0134)						
EI_Full		0.00395					
		(0.0207)					
EI_EnEff			-0.00433				
			(0.0122)				
EI_AEP				0.00348			
				(0.0216)			
EI_Transp					-0.00690		
					(0.0130)		
EI_Recy						-0.0237**	
						(0.00965)	
EI_ProGo							-0.0155*
							(0.00805)
GDP	0.0786	0.156	0.140	0.0803	0.114	0.258	0.209
	(0.167)	(0.179)	(0.158)	(0.233)	(0.144)	(0.176)	(0.138)
D1. Fossil Energy	0.396	0.426*	0.504*	0.394	0.577**	0.400	0.425
	(0.271)	(0.246)	(0.254)	(0.261)	(0.262)	(0.239)	(0.260)
Energy imports	-0.109*	-0.141**	-0.127**	-0.111	-0.124**	-0.162**	-0.154***
	(0.0613)	(0.0622)	(0.0548)	(0.0806)	(0.0553)	(0.0691)	(0.0531)
Time-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	427	408	418	390	402	399
No. of Countries	27	27	27	27	27	27	27
No. of Instruments	27	27	27	27	27	27	27
AR1-Test	-1.98	-1.94	-1.62	-1.71	-1.76	-1.52	-1.52
	[0.048]	[0.052]	[0.106]	[0.086]	[0.078]	[0.128]	[0.127]
AR2-Test	-0.74	-0.51	0.15	-0.09	-0.28	0.18	0.17
	[0.462]	[0.608]	[0.880]	[0.929]	[0.779]	[0.857]	[0.863]
Sargan-Test	11.80	15.53	5.40	11.86	8.49	7.10	5.89
	[0.067]	[0.017]	[0.494]	[0.065]	[0.204]	[0.312]	[0.435]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

We tested our main findings concerning EI_Recy and EI_ProGo (sample 1996-2012) for robustness based on country exclusions, instrument changes, time restrictions, and adjusted model specifications. Concerning country exclusion we considered two relevant criteria. First, given that we analyze fossil material usage, we consider the relevance of the domestic fossil industry. Recent studies have shown that this may be related to lower levels of environmental regulation (Stevens, 2019), which could affect the EI-fossil-relationship. Second, we considered the countries' developmental level, as this is generally considered a relevant factor for environmental impact (Stern, 2004). To determine countries with a high level of fossil industry, we computed the Domestic Resource Dependency (DRD) as the share of domestic extraction in fossil DMI (Weisz et al., 2006). For the developmental level, we computed average GDP per capita as a proxy of affluence (Shao et al., 2017). Therefore, we exclude Estonia and

Poland concerning high DRD of fossils. Luxembourg, Denmark, and Ireland were excluded as the most affluent countries. Bulgaria, Romania, and Latvia as the least affluent countries (A7).

When excluding countries, EI_ProGo becomes insignificant in all three cases. The coefficient increases as the high DRD countries are excluded (to -0.0186), while becoming smaller for both excluding the most and least developed countries.[115] For EI_Recy, the results for excluding countries are reported in A7 since relevant changes emerge. In principle, EI_Recy remains significant at the 5% level in all cases. The coefficient slightly decreases when excluding countries based on their developmental level. Nevertheless, in the case of excluding Estonia and Poland, the coefficient jumps upwards in magnitude to -0.035. This could indicate that worsened environmental regulation due to the domestic fossil industry (Stevens, 2019) may be related to less saving of materials via available technologies. Given that lower activity in this EI field would be captured by the variable itself, the changing coefficient implies that innovation in this area is not related to the common reductions of fossil usage in these countries. Such findings would have important implications concerning the relevance of EI, if the effects are strongly dependent on country characteristics. However, these findings should be treated with caution from a methodological perspective, but also because other country characteristics could be the cause - such as being a catch-up country (Gräbner et al., 2018; Günther, 2015).

When changing the instrumentation, the coefficient of EI_ProGo remains fairly stable, while the level of significance ranges between significance at the 10% level and insignificance. Concerning the instrumentation, the result of EI_Recy proved to be very robust. Given strong fossil dynamics in 1998 (section 3.1.), we also tested excluding 1998 from the analysis. The result of EI_Recy remained stable, both in terms of coefficient size and significance. EI_ProGo lost its significance, yet the coefficient also remained stable. Further, we analyzed alternative specifications in two ways. First, we reduced the model to only the LDV, GDP, and Innovation – excluding energy imports and fossil energy. EI_Recy remained significant and similar in magnitude, EI_ProGo lost its significance yet the coefficient size again remained stable. Second, we included as an additional variable the share of the industry sector, to control potential effects of sectoral composition (Carattini et al., 2015). The industry sector proved to be insignificant, and the results of EI_Recy and EI_ProGo where virtually identical to the core model (Table 2), both in terms of coefficient size and significance levels.[116]

[115] The results for country exclusion in the case of EI_ProGo are not reported here.
[116] The results concerning instrument reduction, exclusion of 1998, and specification changes are not reported, as no additional insights were gained.

We continue by discussing our findings concerning further determinants. The lagged dependent variable has a coefficient of ~0.85, and ~0.6 in the full sample (A4), supporting the use of a dynamic model.

GDP is generally considered to lead to increases in material usage, and fossils are considered to depend strongly on the level of economic development (Steinberger et al., 2013, 2010). On the contrary, this dependency is generally discussed to differ across the developmental levels (Steinberger et al., 2013). Our results differ somewhat between the two samples and indicators, which can likely be due to the discussed weight disparities in the fossil variable (Weisz et al., 2006). For RMI, in the full sample the coefficient ranges between ~0.3 and ~0.6 with varying significance levels (A4), while being insignificant throughout for 1996 to 2012 (Table 2). For DMI, the coefficient is smaller in the full sample ranging between ~0.15 and ~0.2, (A5), yet of similar magnitude for 1996-2012 with ~0.15 to ~0.3 (A6). These unclear results could be related both to the choice of specification and model.

To control for changes in the energy supply structure[117] we included the share of fossil energy in the energy supply. Given the non-stationarity in levels we included the variable in first-differences. The coefficient ranges between ~0.4 and ~0.6 in Table 2, and is somewhat larger for the full sample in the case of RMI. For DMI (A5 and A6) the coefficient is around 1. Hence, given that the variable is included in first-differences, an acceleration of one percentage point is associated with a 1% increase of fossil DMI, and a 0.4 to 0.6% increase of RMI. The closer coupling in the case of DMI may be related to the consideration that the upstream requirements included in imported commodities may reduce the fossil share that is used for energy generation, compared to the alternative use of fossils as raw material (Weisz et al., 2006).

As shown in section three, the substitution of coal by oil and gas should be considered a potentially intervening dynamic for our analysis. For this reason, we used the sample starting in 1996, in order to avoid the strong changes in the early 90s to influence our results. Further, given the general tendency within European economies to substitute domestic coal via fossil fuel imports,[118] we included energy imports[119] as a control variable. It should capture substitution dynamics beyond the exclusion of the first years in our sample. Our estimation results support this consideration, as energy imports are mostly significant (Table 2) with a

[117] For specific EI areas such as EI_Recy it is not assumed that an effect of EI should be changes in the relevance of fossil energy. Hence, if such changes would not be controlled for and correlated with EI in the respective field, results could be biased.

[118] See e.g. https://www.eea.europa.eu/data-and-maps/indicators/net-energy-import-dependency/net-energy-import-dependency-assessment-2 [accessed July 12, 2019].

[119] Net energy imports as share of energy use.

coefficient of ~-0.15. This indicates that increasing net energy imports by one percentage point reduces fossil usage by 0.15%. One explanation could be that higher dependence on the world market is associated with less secure energy supply (Zhao and Wu, 2007), which may result in uncertainty and reduced usage. However, especially in the short-term, a country's energy demand is likely inelastic (Zhao and Wu, 2007). Hence, we consider this variable to capture the aforementioned substitution effect within our dependent variable. This interpretation is supported by the fact that within the full sample for RMI (A4), the effect of energy imports is even larger with the coefficient ranging between ~-0.25 and ~-0.4. This likely relates to the strong substitutional dynamics in the early 90s.

5.6 Discussion and Conclusion

In this paper we analyzed the effects of green technologies on material usage in European economies between 1990 and 2012. More specifically, we were interested in potentially different relationships of specific green technology areas with the material groups biomass and fossil fuels. This interest emerges from a number of factors. First, there is a historically close interconnection of biomass and fossil usage to the structure of human societies (Fischer-Kowalski et al., 2014; Haberl et al., 2011). Second, biomass and fossil fuels are crucially relevant for providing energy - both for subsistence and the maintenance of current societal organization (Haberl et al., 2011; Steinberger et al., 2010; Weisz et al., 2006). Third, they contribute to a wide array of fundamental environmental pressures, including greenhouse gas emissions, land use change and impacts on the carbon cycle (Behrens, 2016).

A high degree of relevance is attributed to green innovation in the pursuit of international environmental goals (Acemoglu et al., 2012; European Commission, 2011a; Popp et al., 2010). We considered it important to empirically assess and quantify the effects of green technologies on biomass and fossil usage, due to the pursuits of substituting fossils with biomass (De Besi and McCormick, 2015; Gustavsson et al., 1995; Ingrao et al., 2016). We have utilized data on material inputs to quantify material usage, and patent data to quantify green technologies. Previous work on the environmental effects of environmental innovation focused on the effects on emission indicators or energy intensity.

Our results indicate that green technologies are not associated with significant changes in biomass usage in European economies, although we considered specific areas of green technology. Especially innovation in areas such as alternative energy production, or recycling and reuse, were considered to capture directed effects. In the case of EI_AEP we expected that increases of biomass as an energy source may be related to increased demand (Bird Life International, 2016). However, it has been shown that connecting patent data to actual changes in energy structure may be difficult to capture (Popp et al., 2011). For recycling and reuse we expected reducing effects, given that recycling of e.g. paper should be connected to reduced material demand (Haas et al., 2015). Despite not having found an effect, it would certainly be exaggerated to claim that technology and biomass usage are not related. Rather, we consider that isolation of the effects of green technology on biomass usage is difficult due to several aspects. First, patents are not perfectly related to the actual changes influencing material usage (Popp et al., 2011). Second, a high share of biomass usage is related to nutrition, which is hardly influenced by technological improvements (Haas et al., 2015). Third, biomass as an aggregated indicator is constituted by inherently heterogeneous material groups, which are largely related to agricultural biomass, but also to wood following different determinants (Weisz et al., 2006). Especially given the crucial relevance of nutritional patterns (Weinzettel et al., 2013; Wiedmann et al., 2015), it may be contended from this analysis that technology does not seem to be the key determinant of biomass usage.

Analyzing fossil fuel usage appeared to be rather homogenous, as most fossil materials are used for energy generation (Behrens, 2016; Haas et al., 2015). Nonetheless, we considered levels of heterogeneity arising from different calorific values between material groups (Weisz et al., 2006). In this vein, we analyzed two different samples and included energy imports to control substitutional dynamics within the dependent variable, mostly away from coal towards oil and gas (Weisz et al., 2006). When analyzing the sample from 1996 to 2012 we found two innovation variables to significantly reduce fossil usage. These distinctions may be due to the effect captured by the different innovation variables. Total Inno and EI_Full may suffer from a causal perspective, given that many technologies are included, which clearly do not relate to fossil usage. Therefore finding significant parameters becomes less likely (Wurlod and Noailly, 2016). EI_AEP and EI_Transp may be difficult to capture in such empirical settings, given that changes in the energy supply system or the transportation system are fundamental and large-scale socio-technical changes that could be hard to capture. Nevertheless, the effects of these technology areas on fossil usage are unquestionable, which is also proven by the effect of the energy structure variable on fossil usage. By contrast, the case of EI_EnEff appears more puzzling, although larger time-lags concerning e.g. the renewal of building stocks seem plausible. Innovation in areas such as EI_Recy and EI_ProGo are likely to be closely associated with incremental improvements, which can be implemented promptly on a firm-level and directly relate to reductions of fossil materials. Given that most fossil materials are used for energy generation and are less available for recycling (Haas et al., 2015), these effects may be related to less energy need, or related effects. Identifying the exact causal relationships between technologies and fossil reductions is beyond the scope of this study; yet it seems to be an interesting avenue for more detailed research on these technologies. Interestingly, the significant effects of EI_Recy and EI_ProGo are exclusively found for Raw Material Input, not for Direct Material Input, where upstream flows are not accounted for. One explanation could be that larger amounts of fossils are embedded in imports for RMI. This could amplify the effects of recycling or reusing materials when upstream flows are reduced as well, which is not sufficiently accounted for in the DMI indicator.

There are avenues for future research that emerge from our analysis. First, as our results indicate that innovation stocks in most green technology areas are not significantly related to reductions, research on the identification and implementation of technologies proven to reduce material usage should be strengthened. A more in-depth understanding as to why environmentally beneficial technologies may not come to fruition is certainly needed. Second, from a methodical perspective, measuring innovation could be conducted differently by further studies. Considering neighboring effects – i.e. that innovations of one country will also be applied or at least affect a closely connected country – could complement our present study. Also, a further possibility to generate a knowledge stock variable could be the usage of bibliometric data. Therefore, the amount and development of certain technical publications, for example, could be extracted and operationalized from the relevant literature data bases. Last, our discussion on country differences (see section 5.2.) should provide motivation to conduct similar analyses on other country samples, in order to gain insights on the role that institutional factors play for the environmental effects of green technologies.

From a global perspective, researchers have stated that the shift to biomass instead of fossil fuels is an indispensable step towards sustainability (Haberl et al., 2011). Despite the limitations of this study, our results cast some doubt on the key role green tech should have played in this transformation so far. These results are complementary to established considerations, which figure energy as fundamental input for economic growth (Ayres et al., 2003; Haberl et al., 2011; Murphy and Hall, 2011). Given the dependence of our societal structure on economic growth and fossil utilization as a 'cheap' energy source (Haberl et al., 2011; Murphy and Hall, 2011), some researchers question technological improvements as being "too technical in kind to materialize" (Haberl et al., 2011, p. 8), since associated changes in societal organization would be inevitable (Haberl et al., 2011). Hence, the core task for years to come seems to be directing technical progress – to increase efficiency and reduce environmental pressure without giving rise to increased usage. The merits of green technical progress will only come to fruition if the societal direction is in line with the direction of technological change.

Appendix

Table A1: Descriptive statistics

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max	Source
Biomass Direct Material Input (DMI Biomass)	Tons	606	6.93e+07	7.84e+07	378573	3.23e+08	UN Environment International Resource Panel Global Material Flows Database
Biomass Raw Material Input (RMI Biomass)	Tons	606	1.04e+08	1.33e+08	1109555	5.75e+08	UN Environment International Resource Panel Global Material Flows Database
Fossils Direct Material Input (DMI Fossils)	Tons	604	8.58e+07	1.09e+08	797000	5.65e+08	UN Environment International Resource Panel Global Material Flows Database
Fossils Raw Material Input (RMI Fossils)	Tons	604	1.02e+08	1.26e+08	542145	5.95e+08	UN Environment International Resource Panel Global Material Flows Database
Agricultural Intensity:[120] Sector Share in Gross Value Added	Share	620	.0345	.0281	.0028	.1587	Cambridge Econometrics European Regional Database (ERD)
GDP	Billions of Euro	620	384.00	601.25	2.80	2539.85	Cambridge Econometrics European Regional Database (ERD)
EI_Full	Stock	621	1449.74	3868.92	0	32174.14	PATSTAT 2017b
EI_AEP	Stock	621	521.25	1285.04	0	10342.2	PATSTAT 2017b
EI_Transp	Stock	621	192.04	614.47	0	6008.21	PATSTAT 2017b
EI_Recy	Stock	621	83.07	194.10	0	1309.30	PATSTAT 2017b
EI_EnEff	Stock	621	285.89	768.56	0	7326.65	PATSTAT 2017b
EI_ProGo	Stock	621	114.72	295.39	0	2658.38	PATSTAT 2017b
Total Inno	Stock	621	8541.33	21704.97	.43	167442.2	PATSTAT 2017b
Energy imports (net): Share of energy use	Share	621	.5363	.3081	-.6569	1	World Bank World Development Indicators
Fossil fuel energy consumption: Share of total energy use	Share	617	.7720	.1797	.1888	1	World Bank World Development Indicators

[120] Share of the Agriculture Sector in Gross Value Added.

Table A2: Unit Roots

	Fisher ADF Inv. X2	**Fisher ADF** Inv. N	**Fisher ADF** Inv. L	**Fisher ADF** M. Inv. X2
Biomass Direct Material Input (DMI Biomass)	171.2216 [0.0000]	-8.3902 [0.0000]	-8.8128 [0.0000]	11.2797 [0.0000]
Biomass Raw Material Input (RMI Biomass)	156.7622 [0.0000]	-7.4689 [0.0000]	-7.9136 [0.0000]	9.8883 [0.0000]
Fossils Direct Material Input (DMI Fossils)	135.5247 [0.0000]	-6.4446 [0.0000]	-6.5406 [0.0000]	7.8447 [0.0000]
Fossils Raw Material Input (RMI Fossils)	215.2174 [0.0000]	-8.8106 [0.0000]	-10.838 [0.0000]	15.5131 [0.0000]
Agricultural Intensity:[121] **Sector Share in Gross Value Added**	146.2266 [0.0000]	-7.2012 [0.0000]	-7.3568 [0.0000]	8.8745 [0.0000]
GDP	141.9617 [0.0000]	-7.0293 [0.0000]	-7.1370 [0.0000]	8.4641 [0.0000]
EI_Full	128.59 [0.0000]	-4.95 [0.0000]	-5.55 [0.0000]	7.18 [0.0000]
EI_AEP	109.03 [0.0000]	-4.15 [0.0000]	-4.46 [0.0000]	5.30 [0.0000]
EI_Transp	67.65 [0.0488]	-0.98 [0.1625]	-0.86 [0.1954]	1.77 [0.0388]
EI_Recy	120.24 [0.0000]	-4.87 [0.0000]	-5.12 [0.0000]	6.37 [0.0000]
EI_EnEff	94.28 [0.0006]	-1.84 [0.0325]	-1.85 [0.0333]	3.88 [0.0001]
EI_ProGo	126.60 [0.0000]	-4.35 [0.0000]	-5.21 [0.0000]	6.99 [0.0000]
Total Inno	180.35 [0.0000]	-7.94 [0.0000]	-8.90 [0.0000]	12.16 [0.0000]
Energy imports (net)	144.4517 [0.0000]	-6.6384 [0.0000]	-6.9846 [0.0000]	8.7037 [0.0000]
Fossil fuel energy consumption	91.4306 [0.0011]	-2.5773 [0.0050]	-2.6620 [0.0043]	3.6018 [0.0002]

Variables used are in logarithm or share.

Fisher-ADF: *The Fisher-type unit-root tests are based on augmented Dickey–Fuller (Fisher-ADF) tests with drift and one lag; the null hypothesis is that "all panels contain unit-roots"; the test does not require a balanced panel. Statistics and respective p-values (in square brackets) are reported for each type of Fisher test: inverse chi-squared, inverse normal, inverse logit and modified inverse chi-squared.*

Δ is the first difference operator*.*

[121] Share of the Agriculture Sector in Gross Value Added.

Table A3: GMM results for DMI Biomass for all countries from 1990 to 2012

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model	AB	AB	AB	AB	AB	AB	AB
Dep. Var.	DMI Biomass	DMI Biomass	DMI Biomass	DMI Biomass	DMI Biomass	DMI Biomass	DMI Biomass
L1. DMI Biomass	0.514	0.532	0.636**	0.519	0.741***	0.642*	0.596
	(0.343)	(0.323)	(0.269)	(0.331)	(0.248)	(0.333)	(0.383)
Total Innovation	-0.0303						
	(0.0404)						
EI_Full		-0.0335					
		(0.0413)					
EI_EnEff			-0.000356				
			(0.0240)				
EI_AEP				-0.0313			
				(0.0392)			
EI_Transp					-0.0254		
					(0.0306)		
EI_Recy						-0.00750	
						(0.0306)	
EI_Manu							-0.0188
							(0.0285)
GDP	0.802**	0.799*	0.658*	0.768*	0.576*	0.583	0.776
	(0.382)	(0.421)	(0.333)	(0.413)	(0.301)	(0.385)	(0.481)
Agricultural Intensity	4.494***	4.297***	3.915***	4.196**	3.400**	3.748**	4.505**
	(1.556)	(1.547)	(1.251)	(1.565)	(1.346)	(1.591)	(2.073)
Time-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	552	550	513	530	497	501	495
No. of Countries	27	27	27	27	27	27	27
No. of Instruments	36	36	36	36	36	36	36
AR1-Test	-1.74	-1.87	-2.29	-1.90	-2.17	-2.02	-1.75
	[0.082]	[0.062]	[0.022]	[0.058]	[0.030]	[0.044]	[0.081]
AR2-Test	0.89	0.98	1.08	1.03	1.10	0.74	0.89
	[0.374]	[0.325]	[0.281]	[0.304]	[0.270]	[0.459]	[0.371]
Sargan-Test	7.08	5.83	17.45	5.98	12.35	9.67	13.45
	[0.793]	[0.885]	[0.095]	[0.874]	[0.338]	[0.560]	[0.265]s

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Table A4: GMM results for RMI Fossils for all countries from 1990 to 2012

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model	AB	AB	AB	AB	AB	AB	AB
Dep. Var.	RMI Fossils	RMI Fossils	RMI Fossils	RMI Fossils	RMI Fossils	RMI Fossils	RMI Fossils
L1. RMI Fossils	0.306	0.285	0.581***	0.576***	0.671***	0.630***	0.620***
	(0.202)	(0.219)	(0.209)	(0.160)	(0.152)	(0.124)	(0.131)
Total Innovation	0.0788						
	(0.0867)						
EI_Full		0.0588					
		(0.0808)					
EI_EnEff			0.00219				
			(0.0198)				
EI_AEP				0.00375			
				(0.0290)			
EI_Transp					0.0148		
					(0.0366)		
EI_Recy						-0.0164	
						(0.0228)	
EI_ProGo							-0.00757
							(0.0178)
GDP	0.277	0.393	0.554*	0.473	0.261	0.423*	0.424**
	(0.443)	(0.429)	(0.284)	(0.284)	(0.271)	(0.215)	(0.169)
D1. Fossil Energy	0.680**	0.802***	0.658**	0.561**	0.746***	0.482*	0.512**
	(0.249)	(0.256)	(0.266)	(0.250)	(0.237)	(0.251)	(0.240)
Energy imports	-0.378***	-0.397**	-0.321*	-0.299*	-0.217*	-0.253**	-0.273**
	(0.107)	(0.163)	(0.174)	(0.158)	(0.127)	(0.112)	(0.104)
Time-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	544	542	511	528	495	499	491
No. of Countries	27	27	27	27	27	27	27
No. of Instruments	32	32	32	32	32	32	32
AR1-Test	-1.38	-1.28	-1.66	-1.88	-1.78	-1.82	-1.76
	[0.167]	[0.199]	[0.096]	[0.060]	[0.075]	[0.069]	[0.078]
AR2-Test	-0.25	-0.26	0.49	0.21	0.22	0.62	0.53
	[0.804]	[0.793]	[0.621]	[0.834]	[0.828]	[0.532]	[0.596]
Sargan-Test	10.77	11.51	2.68	5.24	7.72	1.99	2.67
	[0.096]	[0.074]	[0.848]	[0.514]	[0.260]	[0.921]	[0.849]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Table A5: GMM results for DMI Fossils for all countries from 1990 to 2012

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model	AB	AB	AB	AB	AB	AB	AB
Dep. Var.	DMI Fossils	DMI Fossils	DMI Fossils	DMI Fossils	DMI Fossils	DMI Fossils	DMI Fossils
L1. DMI Fossils	0.780***	0.788***	0.747***	0.666***	0.692***	0.705***	0.725***
	(0.0685)	(0.0720)	(0.0978)	(0.0851)	(0.110)	(0.0592)	(0.122)
Total Innovation	0.00118						
	(0.0156)						
EI_Full		-0.00365					
		(0.0204)					
EI_EnEff			-0.00715				
			(0.0198)				
EI_AEP				-0.0118			
				(0.0294)			
EI_Transp					-0.0200		
					(0.0247)		
EI_Recy						-0.00866	
						(0.0163)	
EI_ProGo							-0.00499
							(0.0146)
GDP	0.219*	0.223	0.159	0.266*	0.146	0.200*	0.189
	(0.119)	(0.133)	(0.145)	(0.140)	(0.155)	(0.0984)	(0.147)
D1. Fossil Energy	0.957**	1.051***	1.092***	0.965**	1.299***	0.996***	1.011**
	(0.408)	(0.371)	(0.356)	(0.350)	(0.381)	(0.357)	(0.370)
Energy imports	-0.100*	-0.100	-0.0822	-0.121*	-0.0754	-0.101*	-0.103
	(0.0577)	(0.0618)	(0.0538)	(0.0658)	(0.0537)	(0.0537)	(0.0691)
Time-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	544	542	511	528	495	499	491
No. of Countries	27	27	27	27	27	27	27
No. of Instruments	37	37	37	37	37	37	37
AR1-Test	-2.64	-2.58	-2.35	-2.32	-2.05	-2.41	-2.22
	[0.008]	[0.010]	[0.019]	[0.020]	[0.041]	[0.016]	[0.026]
AR2-Test	1.14	1.10	0.89	1.11	0.40	1.31	1.16
	[0.254]	[0.269]	[0.372]	[0.266]	[0.692]	[0.191]	[0.245]
Sargan-Test	6.35	11.70	11.36	8.68	3.70	16.65	4.27
	[0.849]	[0.386]	[0.414]	[0.652]	[0.978]	[0.119]	[0.961]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Table A6: GMM results for DMI Fossils for all countries from 1996 to 2012

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Model	AB	AB	AB	AB	AB	AB	AB
Dep. Var.	DMI Fossils	DMI Fossils	DMI Fossils	DMI Fossils	DMI Fossils	DMI Fossils	DMI Fossils
L1. DMI Fossils	0.855***	0.893***	0.683***	0.762***	0.536	0.814***	0.766***
	(0.0875)	(0.0770)	(0.126)	(0.125)	(0.343)	(0.0822)	(0.164)
Total Innovation	-0.00665						
	(0.0172)						
EI_Full		0.00363					
		(0.0184)					
EI_EnEff			-0.0272				
			(0.0185)				
EI_AEP				0.00174			
				(0.0260)			
EI_Transp					-0.0529		
					(0.0501)		
EI_Recy						-0.00179	
						(0.0149)	
EI_ProGo							-0.00399
							(0.0186)
GDP	0.200**	0.141	0.324*	0.212	0.330	0.130	0.192
	(0.0766)	(0.106)	(0.172)	(0.166)	(0.345)	(0.111)	(0.163)
D1.Fossil Energy	0.867**	0.870**	0.942***	0.856**	1.129***	0.866**	0.898**
	(0.395)	(0.405)	(0.327)	(0.364)	(0.339)	(0.368)	(0.356)
Energy imports	-0.124***	-0.109**	-0.167***	-0.132***	-0.165	-0.121**	-0.144**
	(0.0436)	(0.0441)	(0.0549)	(0.0472)	(0.104)	(0.0448)	(0.0590)
Time-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	427	427	408	418	390	402	399
No. of Countries	27	27	27	27	27	27	27
No. of Instruments	31	31	31	31	31	31	31
AR1-Test	-2.59	-2.53	-2.45	-2.30	-1.61	-2.35	-2.26
	[0.010]	[0.011]	[0.014]	[0.021]	[0.106]	[0.019]	[0.024]
AR2-Test	1.03	0.95	0.94	0.92	0.36	1.20	1.13
	[0.303]	[0.341]	[0.346]	[0.359]	[0.722]	[0.231]	[0.259]
Sargan-Test	18.00	10.20	13.62	17.69	11.49	19.79	9.08
	[0.055]	[0.423]	[0.191]	[0.060]	[0.321]	[0.031]	[0.525]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

Table A7: Robustness checks for RMI Fossils / EI_Recy results from 1996 to 2012

	(1)	(2)	(3)	(4)
Criteria	None	High DRD	High GDP pc	Low GDP pc
Countries excluded	None	EE & PL	LU & DK & IE	BG & RO & LV
Dep.Var.	RMI Fossils	RMI Fossils	RMI Fossils	RMI Fossils
L1. RMI Fossils	0.825***	0.647**	0.805***	0.828***
	(0.113)	(0.245)	(0.108)	(0.127)
EI_Recy	-0.0237**	-0.0347**	-0.0181**	-0.0211**
	(0.00965)	(0.0164)	(0.00851)	(0.0100)
GDP	0.258	0.600	0.208	0.251
	(0.176)	(0.406)	(0.173)	(0.189)
D1. Fossil Energy	0.400	0.576**	0.506*	0.276
	(0.239)	(0.211)	(0.266)	(0.241)
Energy imports	-0.162**	-0.260*	-0.222***	-0.152*
	(0.0691)	(0.142)	(0.0603)	(0.0839)
Time-effects	Yes	Yes	Yes	Yes
Observations	402	370	354	371
No. of Countries	27	25	24	24
No. of Instruments	27	27	27	27
AR1-Test	-1.52	-1.41	-1.32	-1.50
	[0.128]	[0.160]	[0.186]	[0.132]
AR2-Test	0.18	0.13	0.40	0.33
	[0.857]	[0.900]	[0.689]	[0.745]
Sargan-Test	7.10	7.04	5.35	8.69
	[0.312]	[0.317]	[0.500]	[0.192]

*Robust standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1*

A8: Technology Classes of Specific EI Domains

List 1: Alternative Energy Production

IPC	IPC	IPC	IPC	CPC
A01H	C12N 9/32	F21S 9/03	H01M 14/	Y02E 10/
A62D 3/02	C12N 9/34	F22B 1/	H01M 2/02	Y02E 50/
B01D 53/	C12N 9/36	F23B 90/	H01M 2/04	Y02E 20/
B09B	C12N 9/38	F23G 5/	H01M 4/86	
B60K 16/	C12N 9/40	F23G 7/	H01M 4/87	
B60L 8/	C12N 9/42	F24D 11/	H01M 4/88	
B63B 35/	C12N 9/44	F24D 15/04	H01M 4/89	
B63H 13/	C12N 9/46	F24D 17/	H01M 4/90	
B63H 19/02	C12P 5/02	F24D 19/	H01M 4/91	
B63H 19/04	C12P 7/06	F24D 3/	H01M 4/92	
C01B 33/02	C12P 7/07	F24D 5/	H01M 4/93	
C01B 33/03	C12P 7/08	F24F 12/	H01M 4/94	
C02F 1/14	C12P 7/09	F24F 5/	H01M 4/95	
C02F 1/16	C12P 7/10	F24H 4/	H01M 4/96	
C02F 11/04	C12P 7/11	F24S	H01M 4/97	
C02F 11/14	C12P 7/12	F24T	H01M 4/98	
C02F 3/28	C12P 7/13	F24V 30/	H01M 8/	
C02M 1/107	C12P 7/14	F24V 40/	H02J 7/35	
C02M 1/113	C12P 7/64	F24V 50/	H02K 7/18	
C07C 67/	C21B 5/06	F25B 27/	H02N 10/	
C07C 69/	C23C 14/14	F25B 30/	H02S	
C10B 53/	C23C 14/16	F26B 3/		
C10G	C23C 14/18	F27D 17/		
C10J	C23C 14/20	F28D 17/		
C10L 1/	C23C 16/24	F28D 18/		
C10L 3/	C30B 29/06	F28D 19/		
C10L 5/	D21C 11/	F28D 20/		
C10L 9/	D21F 5/20	G02B 7/183		
C11C 3/10	E02B 9/	G05F 1/67		
C12N 1/13	E04D 13/	H01G 9/20		
C12N 1/15	E04H 12/	H01L 25/		
C12N 1/21	F01K	H01L 27/142		
C12N 15/	F01N 5/	H01L 27/30		
C12N 5/10	F02C 1/05	H01L 31/02		
C12N 5/12	F02C 1/06	H01L 31/03		
C12N 5/14	F02C 3/28	H01L 31/04		
C12N 5/16	F02G 5/	H01L 31/05		
C12N 5/18	F03B	H01L 31/06		
C12N 5/20	F03C	H01L 31/07		
C12N 5/22	F03D	H01L 51/42		
C12N 5/24	F03G 4/	H01L 51/43		
C12N 5/26	F03G 5/	H01L 51/44		
C12N 5/28	F03G 6/	H01L 51/45		
C12N 9/24	F03G 6/	H01L 51/46		
C12N 9/26	F03G 7/04	H01L 51/47		
C12N 9/28	F03G 7/05	H01L 51/48		
C12N 9/30	F21L 4/	H01M 12/		

List 2: Energy efficiency

IPC	IPC	CPC
B60K 6/10	E04F 13/12	Y02E 40/
B60K 6/28	E04F 13/14	Y02B 20/
B60K 6/30	E04F 13/15	Y02B 30/
B60L 3/	E04F 13/16	Y02B 40/
B60L 50/30	E04F 13/18	Y02B 50/
B60W 10/26	E04F 15/18	Y02B 60/
C09K 5/	E04F 15/20	Y02B 70/
E04B 1/62	E06B 3/263	Y02B 80/
E04B 1/64	E06B 3/267	Y02B 90/
E04B 1/66	E06B 3/273	Y02E 60/
E04B 1/68	E06B 3/277	Y02E 70/
E04B 1/70	F03G 7/08	Y02P 10/25
E04B 1/72	F21K 99/	Y02P 10/26
E04B 1/74	F21L 4/02	Y02P 10/27
E04B 1/76	F24H 7/	Y02P 10/28
E04B 1/78	F28D 20/	Y02P 10/29
E04B 1/80	G01R	Y02P 20/121
E04B 1/82	H01G 11/	Y02P 20/122
E04B 1/84	H01L 33/	Y02P 20/123
E04B 1/86	H01L 51/5	Y02P 20/124
E04B 1/88	H01M 10/44	Y02P 20/125
E04B 1/90	H01M 10/46	Y02P 20/126
E04B 1/92	H02J	Y02P 20/127
E04B 1/94	H05B 33/	Y02P 20/129
E04B 1/98		Y02P 20/131
E04B 2/		Y02P 20/132
E04B 5/		Y02P 40/121
E04B 7/		Y02P 40/123
E04B 9/		Y02P 60/14
E04C 1/40		Y02P 60/15
E04C 1/41		Y02P 70/143
E04C 2/284		Y02P 70/145
E04C 2/288		Y02P 70/163
E04C 2/292		Y02P 70/24
E04C 2/296		Y02P 70/261
E04D 1/28		Y02P 70/263
E04D 13/16		Y02P 70/623
E04D 3/35		Y02P 70/635
E04F 13/08		Y02P 70/639
E04F 13/09		Y02P 70/647
E04F 13/10		Y02P 80/1

List 3: Recycling and Reuse

IPC	IPC	CPC
A43B 1/12	C21B 3/08	Y02E 50/3
A43B 21/14	C21B 3/10	Y02P 10/21
B03B 9/06	C22B 19/28	Y02P 10/22
B22F 8/	C22B 19/30	Y02P 10/23
B29B 17/	C22B 25/06	Y02P 10/24
B29B 7/66	C22B 7/	Y02P 20/147
B30B 9/32	C25C 1/	Y02P 20/148
B62D 67/	D01F 13/	Y02P 20/149
B65D 65/46	D01G 11/	Y02P 20/58
B65H 73/	D21B 1/08	Y02P 60/87
C03B 1/02	D21B 1/10	Y02P 70/179
C03C 6/02	D21B 1/32	Y02P 70/24
C03C 6/08	D21C 5/02	Y02P 70/263
C04B 11/26	D21H 17/01	Y02P 70/267
C04B 18/04	H01B 15/	Y02P 70/279
C04B 18/06	H01J 9/50	Y02P 70/625
C04B 18/08	H01J 9/52	Y02P 70/627
C04B 18/10	H01M 10/54	Y02P 70/629
C04B 18/12	H01M 6/52	Y02P 70/633
C04B 18/14		Y02P 70/649
C04B 18/16		Y02P 70/651
C04B 18/18		Y02P 70/653
C04B 18/20		Y02P 80/40
C04B 18/22		Y02W 30/5
C04B 18/24		Y02W 30/6
C04B 18/26		Y02W 30/7
C04B 18/28		Y02W 30/8
C04B 18/30		Y02W 30/9
C04B 33/132		Y02W 90/2
C04B 33/135		
C04B 33/138		
C04B 7/24		
C04B 7/26		
C04B 7/28		
C04B 7/30		
C05F		
C08J 11/		
C09K 11/01		
C10G 1/10		
C10L 5/46		
C10L 5/48		
C10M 175/		
C11B 11/		
C11B 13/		
C14C 3/32		
C21B 3/04		
C21B 3/06		

List 4: Transportation

List 5: Production or Processing of Goods

IPC	**IPC**	**CPC**	**CPC**
B60K 16/	F16H 48/14	Y02T	Y02P
B60K 6/	F16H 48/16		
B60L 11/18	F16H 48/18		
B60L 7/10	F16H 48/19		
B60L 7/12	F16H 48/20		
B60L 7/14	F16H 48/22		
B60L 7/16	F16H 48/24		
B60L 7/18	F16H 48/26		
B60L 7/20	F16H 48/27		
B60L 7/22	F16H 48/28		
B60L 8/	F16H 48/29		
B60L 9/	F16H 48/30		
B60W 20/	H02J 7/		
B61	H02K 29/08		
B62D 35/	H02K 49/10		
B62K			
B62M 1/			
B62M 3/			
B62M 5/			
B62M 6/			
B63B 1/34			
B63B 1/36			
B63B 1/38			
B63B 1/40			
B63H 13/			
B63H 16/			
B63H 19/02			
B63H 19/04			
B63H 21/18			
B63H 9/			
B64G 1/44			
F02B 43/			
F02M 21/02			
F02M 21/04			
F02M 21/06			
F02M 27/02			
F16H 3/			
F16H 48/05			
F16H 48/06			
F16H 48/08			
F16H 48/10			
F16H 48/11			
F16H 48/12			

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Appendix A: Personal contributions to the papers of the cumulative dissertation

Do European Firms Obey the Rules? Environmental Innovativeness in Light of Institutional Frameworks (Chapter 2)

This paper is joint work with Judyta Lubacha. It was designed and conducted jointly from the beginning, with both authors contributing similarly to almost every step in the process. However, data processing and data analysis was solely conducted by me due to confidentiality of CIS micro data.

The Impact of Environmental Innovation on Carbon Dioxide Emissions (Chapter 3)

This paper is joint work with Daniel Töbelmann. It was designed and conducted jointly from the beginning, with both authors contributing equally to all steps in the process.

About the Relationship Between Green Technology and Material Usage (Chapter 4)

This paper was written by me as a sole author.

Natural Resources and Technology – on the Mitigating Effect of Green Tech (Chapter 5)

This paper is joint work with Daniel Töbelmann and Jutta Günther. It is largely based on my own work, especially concerning conceptualization and empirical work. The literature research, empirical design, and writing of the manuscript were jointly conducted.

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I dedicate this work to the endeavour of making this world a better place, to reduce suffering and expand the possibilities for happiness and joy. I dedicate it particularly to all sentient beings – humans and animals alike - who suffer from recklessness, the misuse of power, or the lack of knowledge by those who they are influenced by. While being insufficient of solving the large problems and injustices that are going on, this work is written in the belief that knowledge and moral combined can pave the way to substantially improving the conditions on planet Earth.

This thesis is the product of more than three years of doctoral studies at the University of Bremen. During this time, I encountered many friendly and supportive people, who all made in one way or the other a contribution to this thesis. I am extremely grateful to my supervisor, Jutta Günther, who enabled me to take on doctoral studies as an undergraduate student. Further, from the first moment on she put trust into me and my capabilities encouraging to not get too distracted by what others say. She never failed to provide with motivation and guidance whenever discussing on both science and life. I am thankful for the inspiring and appreciative atmosphere from which many great experiences emerged for which I am immensely thankful to her.

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