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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 Classifications

Q01 ; Q55 ; Q56 ; Q58

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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,[1] 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

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

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

2. Literature Reviews

This paper draws upon the literature on the environmental effects of Environmental Innovation (EI)[2], 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

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

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 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,[3] 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

[3] 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.

(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[4] (Behrens, 2016). 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 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[5]. 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.

[4] In 2013.
[5] Ceteris paribus.

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[6]. 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 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[7]. We extract data on domestic extraction and imports and calculate RMI by adding

[6] Concerning the indicator Raw Material Input (RMI).

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

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 $s + 1$, 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, 1998; 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[8].

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 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).

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

[8] The b refers to the autumn version.

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.

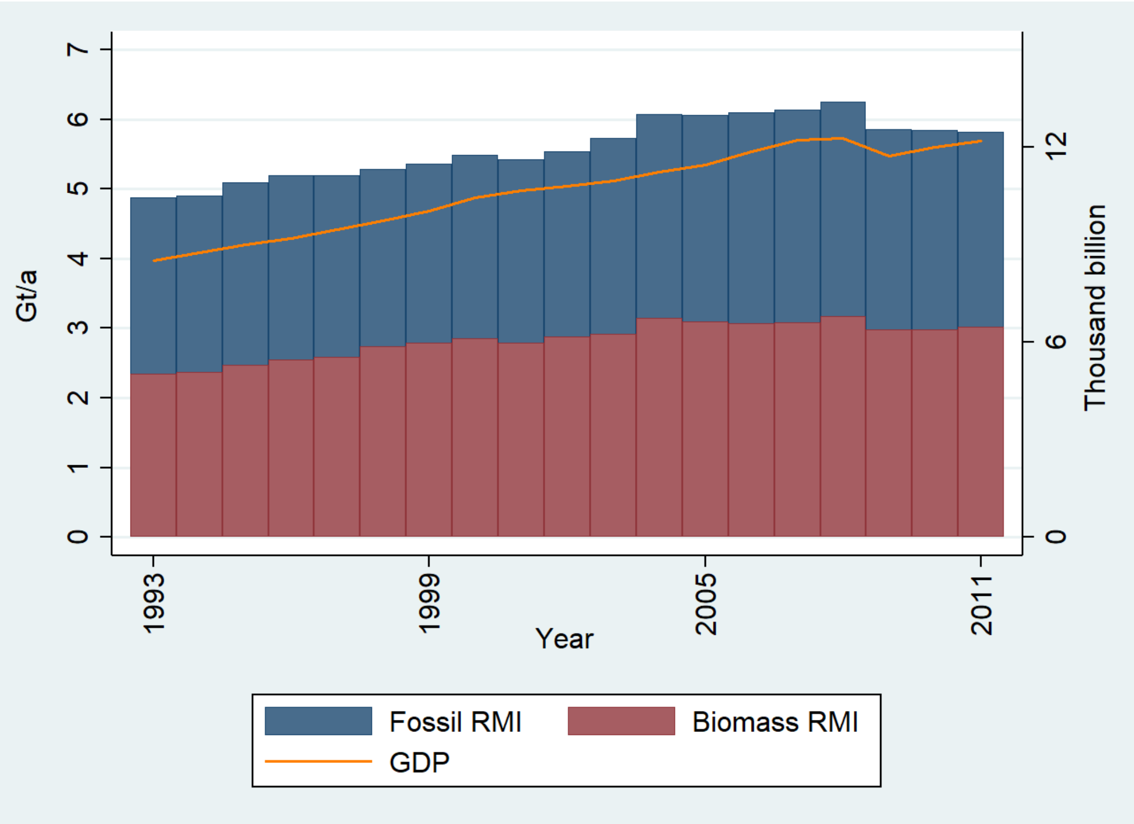

Figure 1: RMI and GDP in the EU-27 per year

Note: 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.[9]

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[10].

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[11], 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

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[9] 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.
[10] 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%.
[11] 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.

differences between the subgroups occur as the calorific value of coal only amounts to 30-50% of the calorific value of oil and gas[12] (Weisz et al., 2006). 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[13] 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 hand. Then, we looked at the changes of the gas plus oil share[14]. 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[15] 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[16] 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[17] 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.

[12] Coal produces more CO_2 per unit of energy (Haberl et al., 2011).
[13] As all are still fossil energy carriers.
[14] 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.
[15] Given the definition of the variable, positive average growth directly implies that the share of oil and gas increased to the disadvantage of coal.
[16] Meaning that positive and negative change rates do not cancel out.
[17] Referring to absolute changes as explained in footnote before.

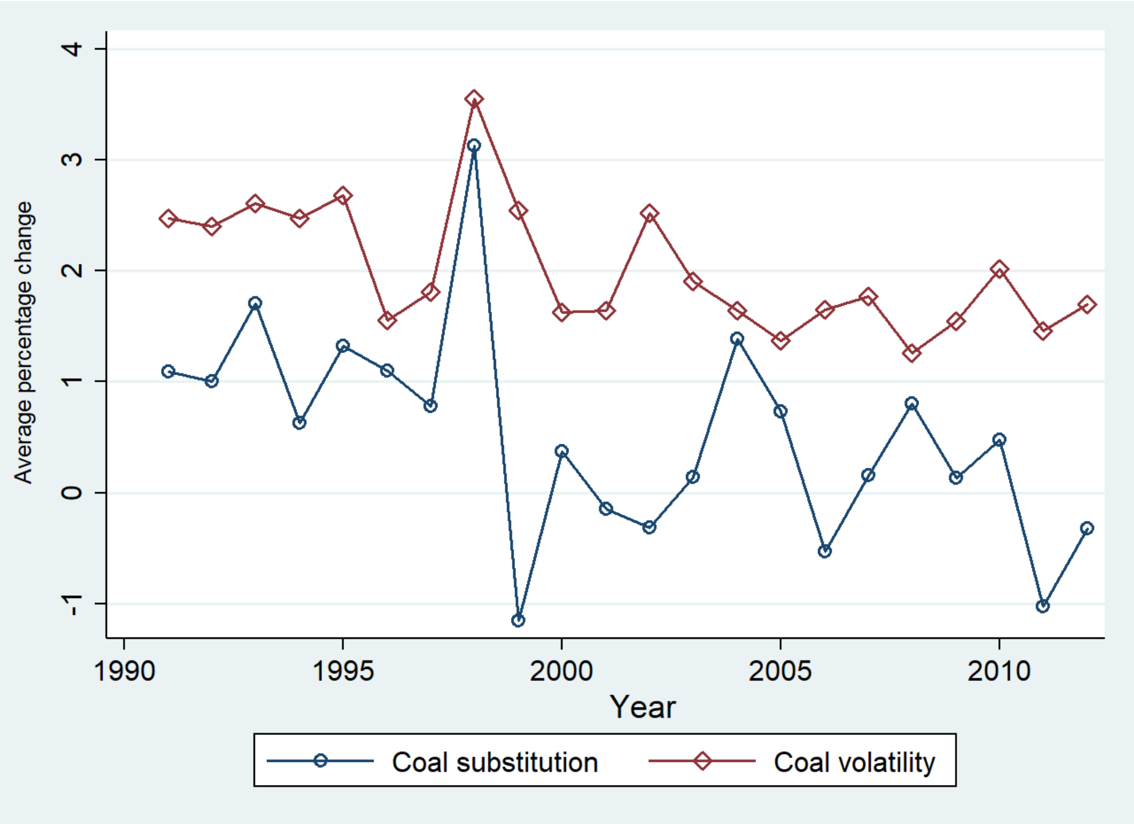

Figure 2: Yearly average changes within fossil DMI across European countries

Note: 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.

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[18]. However, while this relative share is quite constant over time[19], 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 Latvia has on average less than 10%. In general, the share of green innovation (EI_Full) is larger in the non-EU15[20] 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

[18] The descriptive statistics are based on the stock measures of innovation.
[19] 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.
[20] 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.

EI_Transp gains towards 2000 and loses relevance afterwards, EI_ProGo loses towards 2000 and regains afterwards.

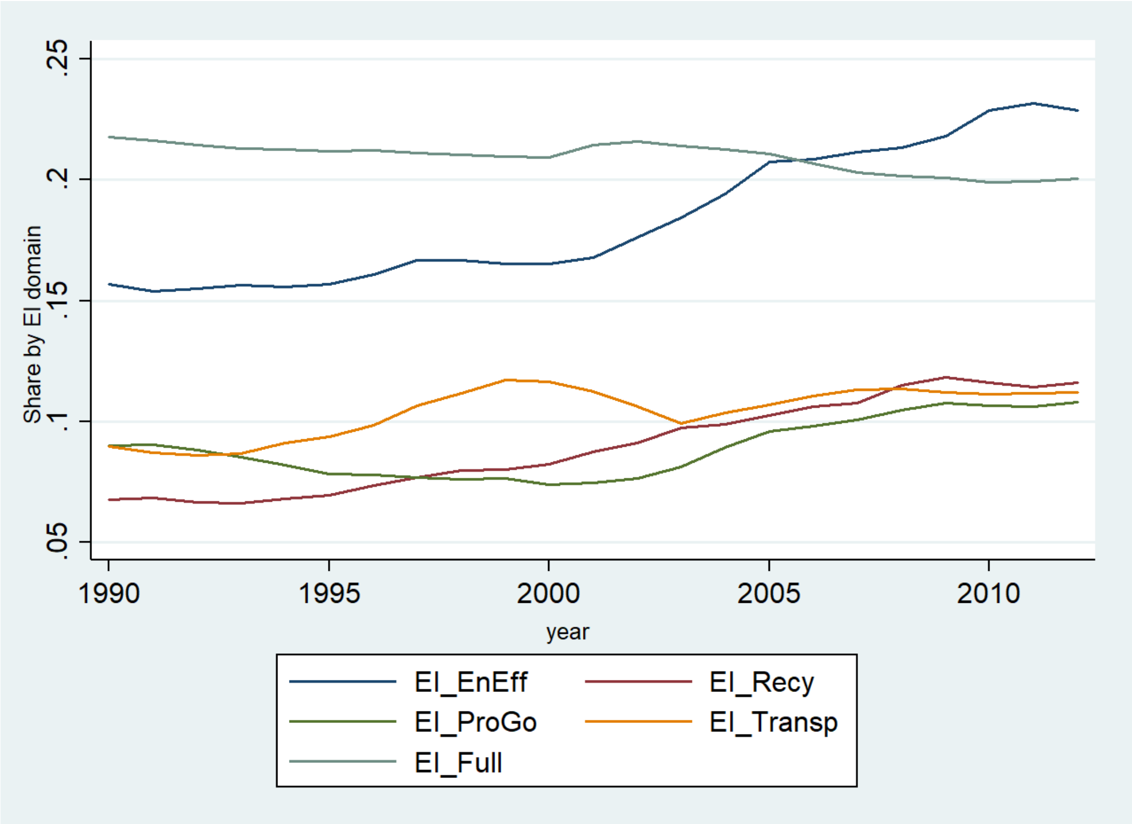

Figure 3: Development of EI domain shares in non-EU15 countries

Note: 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.

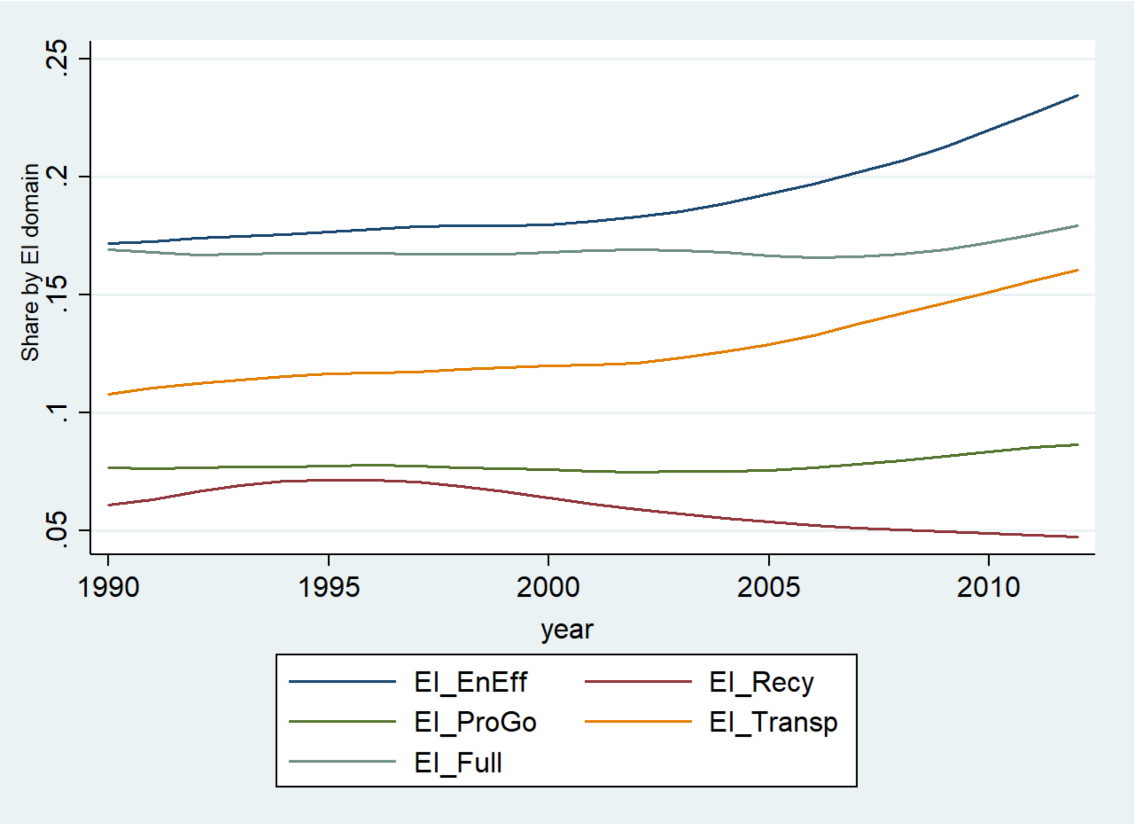

Figure 4: Development of EI domain shares in EU15 countries

Note: 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.

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).

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

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[21] 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[22]. 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:

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

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

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).

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

[21] 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).
[22] 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).

non-stationary. Hence, we included fossil energy in first differences into the model, for both time periods.

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[23] and the Sargan test results support our modelling decisions[24]. 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[25]. 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).

5.1. 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 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

[23] Testing for second-order autocorrelation.
[24] Except for few cases, where however changing the instrumentation would not qualitatively influence the relevant results.
[25] 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.

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[26]. 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.

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

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[27], 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).

[27] 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	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	0.919***	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.[28] 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

[28] The results for country exclusion in the case of EI_ProGo are not reported here.

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[29].

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[30] 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,[31] we included energy imports[32] as a

[29] The results concerning instrument reduction, exclusion of 1998, and specification changes are not reported, as no additional insights were gained.
[30] 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.
[31] 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]
[32] Net energy imports as share of energy use.

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 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.

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.

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Appendix

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[33]: 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

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

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[34]: 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.

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

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

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

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

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

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: Detailed lists of EI domain technology classes

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/		

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

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		

Transportation

IPC	IPC	CPC
B60K 16/	F16H 48/14	Y02T
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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