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Natural resources and technology - on the mitigating effect of green tech

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Natural resources and technology – on the mitigating effect of green tech

Tobias Wendler*, Daniel Töbelmann*, Jutta Günther*

Abstract

Drawing upon the literature on environmental innovation and social metabolism, this paper investigates whether technology can lessen the problem of scarce natural resources. We focus on fossil and biomass materials as important resources for production and consumption. Utilizing a dynamic panel approach, the paper empirically analyses whether environmental innovations reduce the usage of biomass and fossil materials at the national level. Our results suggest that there is no consistent mitigating effect of green technology. Rather more, substantial heterogeneity in technology effects can be found between different types of resources. 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. Further, substitutional dynamics of fossil energy carriers are of major importance.

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

JEL Classification Q01 ; Q55 ; Q56 ; Q58

Declaration of interests: None

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1. Introduction

When you are refueling your car, where is the fuel coming from? Is it biofuels from grain, electrical energy from solar panels, or still gasoline from oil? No matter what you drive and refuel, you are using specific resources, and the car used determines what these resources are. Our socio-metabolic profile, i.e. the ratio in which we use different resources,[1] is intimately related with the technologies we use (Fischer-Kowalski 2011; Haberl et al. 2011). With the large-scale utilization of fossil fuels humanity has become capable of significantly influencing natural processes, leading researchers to label our current era as 'Anthropocene' (Steffen et al. 2007). Due to the environmental crisis, reducing fossil use and even reversing the shift to fossil fuels has been suggested (Fischer-Kowalski 2011; Haberl et al. 2011). A substitution of fossil fuels by biomass is considered as a promising avenue (Gustavsson et al. 1995; Ingrao et al. 2016). To enable such developments, however, new technologies, and particularly specific environmentally beneficial technologies are requested (Acemoglu et al. 2012; Aghion et al. 2016; Hepburn et al. 2018). But what are the actual effects of environmental innovation on the usage of biomass and fossil resources?

In this paper, we aim at disentangling the effects of green innovation on the biomass and fossil fuel usage in European economies. We construct a panel dataset from 1990 to 2012, and utilize a dynamic panel approach. We focus on the 27 European Union (EU) countries,[2] 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.[3] We use indicators of Economy Wide Material Flow Accounting (EW-MFA) to capture the utilization of biomass and fossil resources, as is common in similar applications (Weisz et al. 2006; Fischer-Kowalski et al. 2011; Behrens 2016; Agnolucci et al. 2017). To operationalize environmental innovation, we rely on patent data to construct knowledge stocks (see Section 2.2).

[1] Such as biomass, fossil fuels, metal ores, or non-metallic minerals.
[2] Croatia is not included in our sample since it joined the EU in 2013.
[3] The 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 2008, 2010, 2011a, 2015). 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 2011b).

Our results suggest that the effects of green technologies differ not only by technological field, but by resource type as well. We find no evidence for resource saving effects of green innovation in the case of biomass use. For fossil fuels, we find innovation in the areas recycling & reuse, and the production or processing of goods to have a reducing effect on fossil use, once substitutional dynamics within the fossil composition are controlled for. Further, country characteristics could play a role for the magnitude of the technology effect on fossil use.

A technological change capable of reducing material consumption plays a key role in the pursuits of 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; Jaffe et al. 2002; Popp et al. 2010, 2011; Acemoglu et al. 2012), as environmental problems are not adequately addressable with current technologies (Popp et al. 2010). Hence, particularly environmental innovation (EI) (Barbieri et al. 2016) is of central interest. Empirical studies investigating the environmental effects of EI focus primarily on emissions (Carrión-Flores and Innes 2010; Wang et al. 2012; Weina et al. 2016; Zhang et al. 2017; Ghisetti and Quatraro 2017; Costantini et al. 2017; Cheng et al. 2019; Töbelmann and Wendler 2020; Georgatzi et al. 2020).[4] However, it is evident that economic activity is accompanied by various environmental pressures. Material-use indicators have been considered appropriate to assess such integrated environmental problems (Fischer-Kowalski et al. 2011; Behrens 2016; Agnolucci et al. 2017). Concerning overall resource use, Wendler (2019) finds green innovation to reduce resource use while innovation in general does not. Further, the effects of green innovation are found to be heterogenous across technological fields (Wendler 2019). Nevertheless, it is still up to empirical studies to investigate the concrete effects of green technologies on specific 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; Haberl et al. 2011; Fischer-Kowalski et al. 2014). Biomass was the dominant material group for human use, before its relevance declined strongly within industrial societies (Krausmann et al. 2009; Haberl et al. 2011; Fischer-Kowalski et al. 2014). Fossil fuels were an irrelevant material group within the agrarian regime,[5] but are a key ingredient to the material-use profile of industrial countries

[4] Exceptions are the studies by Wurlod and Noailly (2018) and Wendler (2019).

[5] Three broad 'socio-metabolic regimes' have been distinguished, namely the hunter-gatherer regime, the agrarian regime, and the industrial regime (Haberl et al. 2011; Fischer-Kowalski et al. 2014). The industrial revolution, i.e. the shift to a 'fossil energy system', marks the onset of the industrial regime and led to strong increases in energy and material use, population density, and trends such as urbanization (Haberl et al. 2011; Fischer-Kowalski et al. 2014).

(Haberl et al. 2011; Fischer-Kowalski et al. 2014; 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 (Weisz et al. 2006; Haberl et al. 2011; Schramski et al. 2015). 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).

The remainder of the paper is structured as follows: section 2 introduces the data employed. Section 3 explains the method used in our analysis. Section 4 provides our empirical results, which are then discussed and concluded in section 5.

2. Data

2.1 Material input 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

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

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 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.

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

[7] Data after 2012 is available, however according to the Technical Annex should not be used for statistical analysis, since it might be increasingly projection based.

discuss the dynamics over time of both material groups. Lastly, we will explore the composition of biomass and fossil fuels,[8] 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. Figure 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.

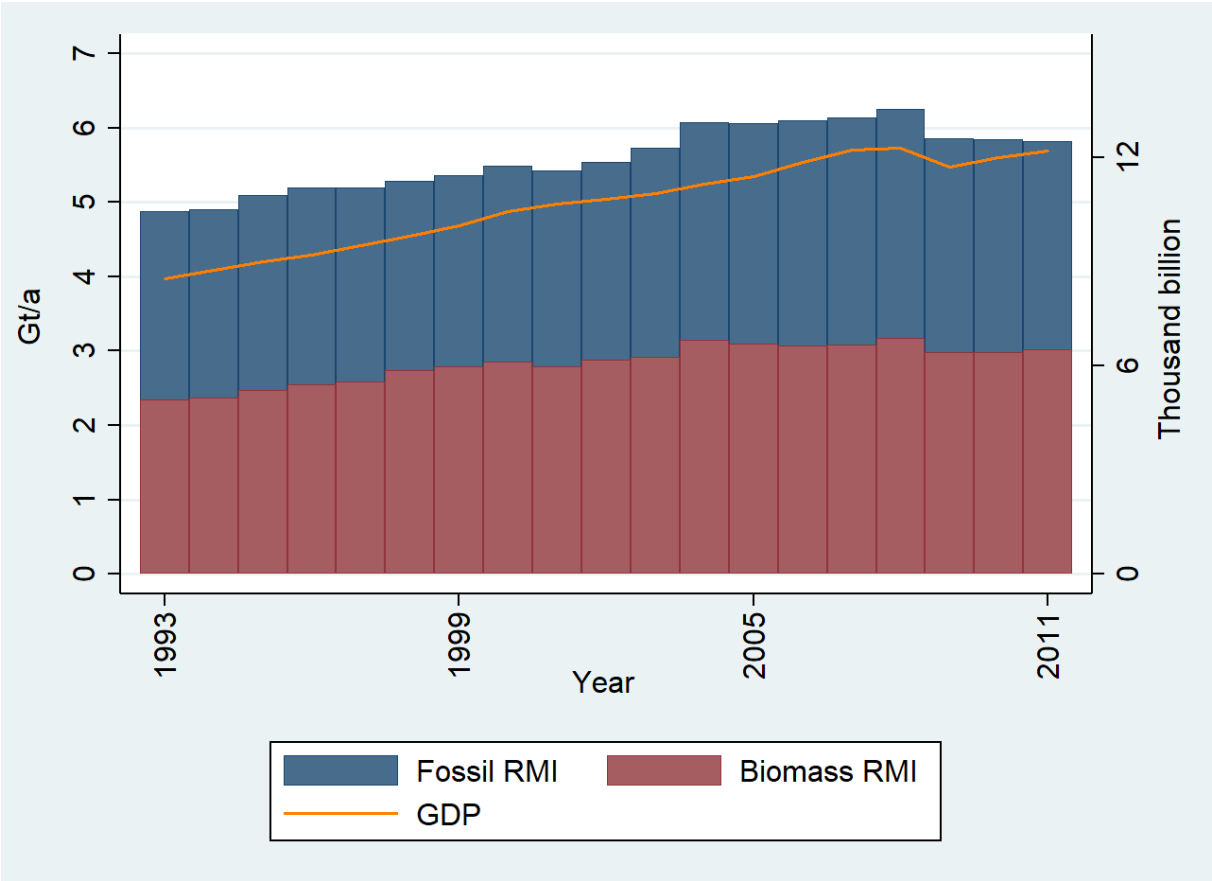

Figure 1. RMI and GDP in the EU-27 per year

[8] Concerning the composition analysis, data on DMI, not RMI, will be used as there is no more detailed data on RMI available.

Notes: 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

[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.

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).[12] 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 Figure 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.

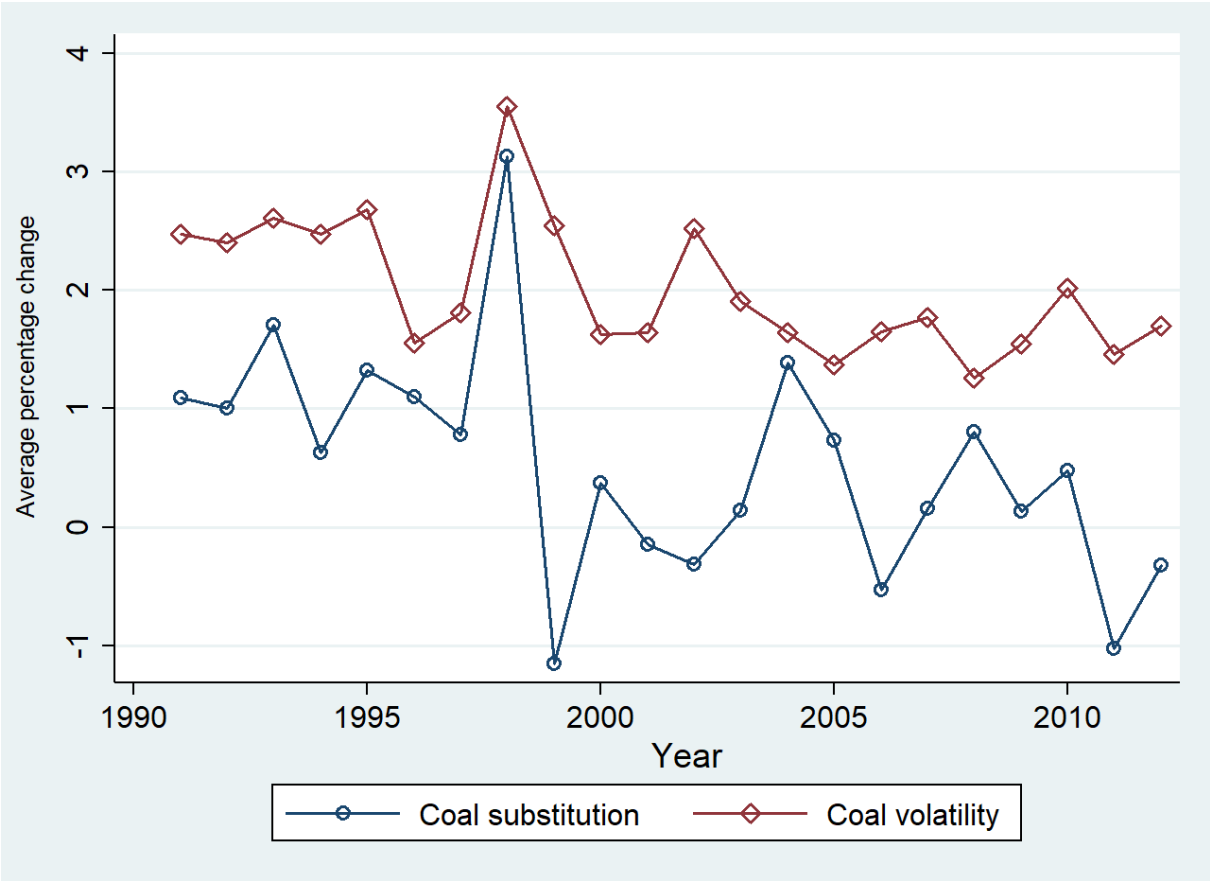

Figure 2. Yearly average changes within fossil DMI across European countries

Notes: 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.

2.2 Patent data

Given our interest in analyzing the effects of green technologies on material usage we utilize patent data on environmental innovation (EI). We construct knowledge stocks as a measure of installed and available technological capabilities (Popp 2002; Popp et al. 2011; Costantini et al. 2017). Following Popp et al. (2011) the knowledge stock is constructed according to the following formula:

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

$ß_1$ 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 (Lanjouw and Mody 1996; Johnstone et al. 2010; Popp et al. 2011; Haščič and Migotto 2015; 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 (Griliches 1990; Dernis and Khan 2004; 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; Wang et al. 2012; Costantini et al. 2017; Wurlod and Noailly 2018). The patent data was retrieved from PATSTAT 2017b.[18]

To distinguish EI from other innovations, we utilize the technological classes of patent applications. The WIPO Green Inventory (GI) (Kruse and Wetzel 2014; Albino et al. 2014; Ghisetti and Quatraro 2017) and the OECD EnvTech indicators (EnvTech) (Haščič and Migotto 2015; Ghisetti and Quatraro 2017; Costantini et al. 2017) have been made available to make such discrimination feasible. However, given the heterogeneity of technologies included in these lists we also use the data on several subdomains of EI as utilized by Wendler (2019), capturing potentially specific technological effects and dynamics. The comprehensive EI variable is constructed by using all technological classes encompassed by the GI and/or the EnvTech (EI_Full). Further, innovation in the area of alternative energy production (EI_AEP) and green technologies relating to transportation (EI_Transp) are considered, since achieving the decarbonization of mobility and energy provision is considered crucial to achieve environmental goals. EI in the area of recycling and reuse (EI_Recy) fundamentally relates to concepts of

[18] The b refers to the autumn version.

resource efficiency and circular economy (European Commission 2015; Haas et al. 2015). Beyond that EI in relation to energy efficiency (EI_EnEff) is used, given the crucial importance of improved energy efficiency to reduce fossil usage. Further, climate change mitigation technologies in the production or processing of goods (EI_ProGo) are operationalized, 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, a variable capturing all innovations (Total Innovation) is used. 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 2018).

2.3 Further data

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 (Appendix A).

3. 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[19] and endogeneity problems - this study employs the one-step difference Generalized Method of Moments (GMM)

[19] 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 2012).

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 (Judson and Owen 1999; Hwang and Sun 2018).

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 2012). 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. 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 (Roodman 2009; 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 (Appendix B). 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.

4. Empirical Results

We now turn to the empirical estimations carried out. To secure the plausibility of our instrumentation choices and results, the AR2-test[20] and the Sargan test results support our modelling decisions.[21] 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 (Costantini et al. 2017; Agnolucci et al. 2017). Further variables are treated as exogenous. We instrumented Innovation with the second to fourth lag.[22] 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; Roodman 2009; Hsiao and Zhou 2017).

4.1 Biomass

We now turn to our estimations concerning the usage of biomass. As indicated in section 2.1, we do focus on the overall sample. The results for all EI variables and Total Innovation can be found in Table 1.[23] 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

[20] Testing for second-order autocorrelation.

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

[22] 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.

[23] For some specifications we find the Sargan test to lie outside the desired realm. For consistency, we reported results for the chosen combination of instruments despite this. Please note that by varying the instrument choices the Sargan test moves into the desired realm, while the results remain stable.

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 (Appendix C) 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 (Weisz et al. 2006; Krausmann et al. 2009; Steinberger et al. 2010; Steinberger and Krausmann 2011). 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 (Weisz et al. 2006; Haas et al. 2015).

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 (Gan et al. 2013; Fernández-Herrero and Duro 2019).

As discussed in section 2, 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.[24] 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% 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.

4.2 Fossils

We continue with our results on fossil material usage. Given our findings in section 2.1, 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.

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

The results are displayed in Table 2. Total innovation and innovation in the areas of EI_Full,[25] 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 (Appendix D), their coefficient sizes are of a similar magnitude, specifically -0.0164 for EI_Recy and -0.0076 for EI_ProGo. It should be noted that for DMI, all innovation variables remain insignificant in both samples (Appendix E and Appendix F).

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

[25] 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.

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 (Appendix G).

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.[26] For EI_Recy, the results for excluding countries are reported in Appendix G 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 (Günther 2015; Gräbner et al. 2018).

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 2.1), we also tested excluding 1998 from the analysis. The result of

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

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.[27]

Crucial for the validity of our estimation approach is the compliance to the sequential exogeneity assumption, which implies the moment conditions. To secure this it is required that sufficiently many lags of the dependent variable are included (Acemoglu et al. 2019). Therefore, we also checked our two significant EI fields with inclusion of two respective three lags of resource use (Appendix H). Our result for EI_Recy remains significant at the 5% level for both additional specifications, with the coefficient increasing in magnitude.[28] The results for EI_ProGo remain virtually identical with two lags included, while increasing in magnitude but losing significance with three lags included.

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 (Appendix D), 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. 2010, 2013). 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 (Appendix D), 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 (Appendix E), yet of similar magnitude for 1996-2012 with ~0.15 to ~0.3 (Appendix F). These unclear results could be related both to the choice of specification and model.

[27] The results concerning instrument reduction, exclusion of 1998, and specification changes are not reported, as no additional insights were gained.

[28] With two lags of resource use, however, the AR2 test fails to reject the absence of serial correlation.

To control for changes in the energy supply structure[29] 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 (Appendix E and Appendix F) 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 2.1, 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,[30] we included energy imports[31] 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 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 (Appendix D), 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.

[29] 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.

[30] See e.g. https://www.eea.europa.eu/data-and-maps/indicators/net-energy-import-dependency/net-energy-import-dependency-assessment-2 [accessed December 20, 2020]

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

5. 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 (Haberl et al. 2011; Fischer-Kowalski et al. 2014). Second, biomass and fossil fuels are crucially relevant for providing energy - both for subsistence and the maintenance of current societal organization (Weisz et al. 2006; Steinberger et al. 2010; Haberl et al. 2011). 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 (Popp et al. 2010; European Commission 2011b; Acemoglu et al. 2012). 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 (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 innovation. Previous work on the environmental effects of environmental innovation focused on the effects on emission indicators, energy intensity, and resource use in general.

There are several 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 as to why environmentally beneficial technologies may not come to fruition is needed. Second, our discussion on country differences (see section 4.1) 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. Lastly, further research on the heterogenous effects of technology on different material groups is required. Given the data availability of our time-series dimension, our chosen estimation approach could not account for econometric issues like parameter heterogeneity or cross-sectional dependence.[32] With increasing data availability and an increasing time-series dimension treating these limitations lends itself as natural extension to assess similar research questions.

[32] Cross-sectional dependence and parameter heterogeneity could be tackled e.g. with the Common Correlated Effects (CCE) estimator (Pesaran 2006). However, the CCE estimator requires strict exogeneity of regressors

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, a high share of biomass usage is related to nutrition, which is hardly influenced by technological improvements (Haas et al. 2015). Second, 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 (Haas et al. 2015; Behrens 2016). 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 2018). 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 in general seem likely, which is also suggested by the effect

(Chudik and Pesaran 2015), and its dynamic version is not applicable with our data characteristics (Chudik and Pesaran 2015; Everaert and De Groote 2016).

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.

Due to the similar empirical setting, our results are well comparable to previous findings on overall resource use (Wendler 2019). While EI_EnEff has been found to reduce overall resource use, we find such effect neither on biomass nor fossil use. On the flipside, for EI_ProGo we find a slightly significant effect on fossil use in our main analysis (Table 2) that is comparable to the findings by Wendler (2019). Further, as for overall resource use EI_Recy turns out to be most clearly connected with reductions in fossil materials. However, the effect of EI_Recy on fossils is substantially smaller compared to effects on overall resource use (Wendler 2019).[33] To sum up, while there are no technology effects found regarding biomass, even for fossils the technology effects are much less pronounced compared to overall resource use. Hence, our results point to heterogenous technology effects on different material groups, demanding further research on those dynamics.

[33] The effect of EI_Recy (compare Table 2) is not sensitive to the inclusion of specific control variables. It remains virtually identical when including only GDP and the share of the industry sector besides the lagged dependent variable.

Appendix

Appendix A - Descriptive statistics

Variable	Unit	Obs	Mean	Std. Dev.	Min	Max	Source
Biomass Direct Material Input (DMI Biomass)	Million Tons	606	69.3	78.4	0.379	323	UN Environment International Resource Panel Global Material Flows Database
Biomass Raw Material Input (RMI Biomass)	Million Tons	606	104	133	1.11	575	UN Environment International Resource Panel Global Material Flows Database
Fossils Direct Material Input (DMI Fossils)	Million Tons	604	85.8	109	0.797	565	UN Environment International Resource Panel Global Material Flows Database
Fossils Raw Material Input (RMI Fossils)	Million Tons	604	102	126	0.542	595	UN Environment International Resource Panel Global Material Flows Database
Agricultural Intensity: 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

Appendix B - 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	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.

Appendix C - 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

Appendix D - 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

Appendix E - 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

Appendix F - 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

Appendix G - 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

Appendix H - Robustness checks for RMI Fossils / EI_Recy & EI_ProGo from 1996 to 2012 with additional lags

	(1)	(2)	(3)	(4)	(5)	(6)
Model	AB	AB	AB	AB	AB	AB
Dep. Var.	RMI Fossils	RMI Fossils	RMI Fossils	RMI Fossils	RMI Fossils	RMI Fossils
L1. RMI Fossils	0.825***	0.729***	0.656***	0.867***	0.842***	0.764***
	(0.113)	(0.127)	(0.140)	(0.0871)	(0.124)	(0.175)
L2. RMI Fossils		0.0677	0.00553		0.0159	-0.0338
		(0.0709)	(0.0865)		(0.0983)	(0.109)
L3. RMI Fossils			0.0893			0.0762
			(0.0694)			(0.0813)
EI_Recy	-0.0237**	-0.0262**	-0.0283**			
	(0.00965)	(0.0101)	(0.0120)			
EI_ProGo				-0.0155*	-0.0164*	-0.0210
				(0.00805)	(0.00828)	(0.0130)
GDP	0.258	0.329**	0.427**	0.209	0.231**	0.341*
	(0.176)	(0.157)	(0.160)	(0.138)	(0.103)	(0.176)
D1. Fossil Energy	0.400	0.409	0.439*	0.425	0.428	0.452*
	(0.239)	(0.243)	(0.233)	(0.260)	(0.262)	(0.249)
Energy imports	-0.162**	-0.184**	-0.221**	-0.154***	-0.161***	-0.201**
	(0.0691)	(0.0716)	(0.0826)	(0.0531)	(0.0565)	(0.0921)
Time-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	402	402	402	399	399	399
No. of Countries	27	27	27	27	27	27
No. of Instruments	27	27	27	27	27	27
AR1-Test	-1.52	-2.84	-2.99	-1.52	-3.49	-3.61
	[0.128]	[0.005]	[0.003]	[0.127]	[0.000]	[0.000]
AR2-Test	0.18	-2.36	-1.24	0.17	-1.50	-0.40
	[0.857]	[0.018]	[0.214]	[0.863]	[0.133]	[0.686]
Sargan-Test	7.10	5.53	2.18	5.89	5.88	3.88
	[0.312]	[0.355]	[0.702]	[0.435]	[0.318]	[0.423]

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

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