Keep up with the Greens: Inventions, Heterogeneous Policy effects and International Spillovers

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Abstract

The achievement of economic and environmental sustainability largely depends on technological change. The literature has theoretically and empirically investigated the extent to which Green technological progress is influenced by varying policy stringency and country commitments, with recent relevant literature advancements predominantly on the microeconomic side. Theory and evidence suggest that countries policy actions might have heterogeneous impacts on technological progress, depending on institutional and economic conditions, among which trade relationships assume a strong importance. The paper investigates whether inventions-policy relationship are heterogeneous across countries, on the basis of a country OECD panel dataset that covers green patents, R&D, human capital, policies and trade over 1983-2013. It also analyses whether inventions inducing spillovers exist, in the form of stimulus a country might receive from the policy actions operated by its main trade partners. Internal and External policies can produce technological effects. Various panel models that take into account for serial correlation and slope heterogeneity are implemented: random coefficient models, constrained and unconstrained seemingly unrelated regressions, which can convey individual country coefficients, and average mean group estimators that capture country heterogeneity by including averages and common factors within the vector of covariates. The statistical and economic meaning and feasibility of cross country heterogeneous effects is the main aim of the paper. Results show that heterogeneity and serial correlation matter. Though the constraints posed by the reduction of poolability are somewhat binding, strong heterogeneity emerges with respect to the effects of R&D, trade and environmental policies towards the generation of green patents. Individual 'innovation function' with idiosyncratic features and different 'models' or clusters are drawn out by the analysis. This signifies that parametric specifications that address cross section heterogeneity and time related factors might enhance both the statistical robustness of results and their specific policy relevance.

Keywords: green inventions, environmental policy, R&D, human capital, trade spillovers, OECD, SURE, slope heterogeneity

1. Introduction

One of the most widely used expression in the economic literature is certainly the well-known "Keep up with the Joneses". According to this expression, originally introduced in 1913 from a comic strip published in the New York Globe that became quickly popular, people tend to look at the consumption habits and standards of their neighbour (the Jones, one of the most common surname in the USA) and take their own consumption decisions so as to maintain similar consumption standards. This idea has been very influential in the economic literature generating a large number of studies on relative consumption that have been applied and tested in many different contexts and to study different economic issues (e.g. inequality, growth, happiness, social and behavioural economics etc..).

The present paper intends to exploit that idea from a different perspective and develop it in a different context. More precisely, rather than adopting a microeconomic approach in which people decide their consumption habits looking at what their neighbours do, we adopt here a macroeconomic approach and investigate whether countries decide their environmental behaviours (i.e. policies and technologies) looking at what their commercial partners do. In this case, therefore, the neighbours are not necessarily the surrounding countries that are geographically closer, but those that have larger and more frequent commercial exchanges with the country at stake. The basic idea underlying the analysis is that the environmental policy adopted by a country and the related level of environmental innovation might depend on what the partners do in terms of environmental policies and innovation. Thus, for instance, if my major partners adopt more stringent environmental policies and invest a lot of resources in eco-innovation/inventions (henceforth, EI), then I might be induced (or forced) to do the same and raise my environmental standards/performance in order to keep exporting to those countries. The analysis hence focuses on possible environmental spillovers at country level, which is why –playing with words- we somehow provocatively replaced in the title "Joneses" with "Greens" (another common surname in English speaking countries) in the popular expression mentioned at the beginning.

To investigate the issue briefly described above, this paper examines the existence and dimension of country's environmental policy spillover effects on the eco-innovation[1] performed by other countries. Hence, the research hypothesis that we intend to test is whether the EI of a country is affected by the stringency of the environmental policy of its main commercial partners and, if so, how. For this purpose, we will estimate the following empirical model, which is theoretically related to Innovation functions (Griliches, 1979, 1990). It is a policy augmented green innovation function (Milliman and Prince, 1989, Jaffe and Stavins, 1997):

$$(EI)i = f[x, (POLICY)i, (POLICY)j*(Xij+Mji)/Yi] \quad (1)$$

where:

EI is the number of green patents per year[2]

x is a vector of explanatory variables (to be defined below, such as R&D, Trade openness, human capital)

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[1] We refer to green inventions, namely green patents. Our Green patent data is related to inventions in the areas: Climate change mitigation technologies related to energy generation, Transmission or distribution Capture, storage, sequestration or disposal of greenhouse gases, Environmental management , Water-related adaptation technologies.

[2] When two countries apply, the patent is shared.

(POLICY)i measures the stringency of the environmental policy of country i.
Environmental policies, of market and non-market based nature, can dynamically sustain the inventions performance given the double eternality setting that characterise green innovations: environmental quality is over-produced by markets (negative externality), while R&D and innovations are usually under produced (positive externality). Market based environmental policy instruments and mixed policy packages (Rogge and Reichardt, 2016) can provide dynamic efficiency, namely generation of invention and innovation, in addition to usual static efficiency properties (OECD, 2011). The dynamic efficiency hypothesis, though relying on simple costs and benefits mechanisms – the benefits of innovating in terms of lower compliance costs and real innovation market benefits, the cost of producing and adopting innovations – should find empirical support case by case. Methodologically speaking, the inclusion and the treatment of environmental policies in GK functions is relevant in a panel data setting, given that (i) its exclusion would cause e major shortcoming in terms of omission of a key variable for innovation, (ii) its inclusion imports into the model a strong cross country heterogeneity and serial correlation as well. Environmental policies, especially in non-homogeneous areas such as the OECD area, follow very diverse patterns and present diverse features. On the other hand, common shocks such as international oil shocks or major environmental agreements or conventions (e.g. Rio convention, Kyoto Protocol, COP21 Paris in 2015) can produce both common (clustered by groups) and specific country effects, namely country specific responses to energy and policies shocks. Summing up, environmental policy effects are includable and treatable as specific country based policies and responses of a country, or a group of counties, to international policy and energy events.

(POLICY)j measures the stringency of the environmental policy of country j

Xij denotes the exports from country i to country j, Mji the imports from i to j and Yi the GDP level of country i.

As a first (and admittedly rough) approximation, in the present version spillover effects will be weighted by each country's degree of openness to trade, that is, the sum of total exports and imports of country i as compared to its GDP level (Xi+Mi/Yi). This is meant to provide a preliminary proxy measure of the importance that the trade channel can play in affecting the country's eco-innovation. The present analysis will then be extended in the future using as weights bilateral exchanges (between countries i and j) rather than the country's overall degree of openness.

To test the aforementioned question we use a set of variables retrieved from a new country panel data base that merges R&D, green patents, environmental policy and trade openness from various sources over a long period of time. The data coverage is 1983-2013 for 17 OECD countries. We focus on high income countries for reasons linked to data availability – our panel data analysis needs pretty long time series and good coverage over innovation and policy variables, and because we aim at investigating policy spillovers, that tend to be more relevant among advanced countries that show some signs of decoupling (Musolesi and Mazzanti, 2013), and between high income and medium-low income countries (UNIDO, 2016, 2018; Gilli et al. 2017). The latter analysis is postponed to future research.

The model is empirically tested using panel data econometric methods that address heterogeneity[3], which is theoretically and empirically a cornerstone argument in the literature about growth, development, innovations (Azariadis and Drazen, 1990, Durlauf et al. 2001 for conceptual insights, Musolesi and Mazzanti, 2013; List and Gallett, 1999 on environment, policy & development dynamics). As it is well known, panel data presents various alternatives to cope with the analysis of individual heterogeneity and omitted or unobserved effects. The key issue is always to specify a model that is able to account for behaviour heterogeneity[4] across individuals and over time in a common 'pool' of data. The various degrees of Poolability and the management of intrinsic trade-offs between different models are the main issue within panel data analysis.

Key specifications are, in a linear additive parametric world: (i) intercept and slopes are constant, error terms capture heterogeneity; (ii) constant slopes but different intercept (one way model, with deterministic or stochastic fixed effects); (iii) constant slopes but different intercepts by individuals and by time (two ways models, again with deterministic or stochastic fixed effects); (iv) intercepts and slopes may vary by individuals; (v) intercepts and slopes may vary by time. Poolability is relaxed moving from i to v. Given that consistency is assured for large T*N dataset, the intrinsic trade off is between higher efficiency in poolable models that estimate a more limited set of parameters and lower efficiency but heterogeneity accounting in models that consider cross section and time related heterogeneity.

SURE econometric techniques (case iv with deterministic effects) are the main tool of investigation in this paper, as well as additional methods that deal with heterogeneity such as mean group and common correlated effect estimators (Eberhardt et al. 2013)[5].

The analysis then starts with fixed effect (two ways) models. SURE models are introduced to (i) increase efficiency of FE models due to the consideration of correlation among units at any given time t; (ii) to verify whether the slope homogeneity assumption is rejected by data and move towards a specification that allows estimating innovation output – R&D, trade, policy effects country by country. Given the increase in the number of estimated parameters, slope heterogeneous models can usually include a more limited set of countries. This empirically depends on the relative length of T with respect to N. This paper starts with T over 1983-2013 and 16 countries.

The paper differs from previous contributions in the literature that studies the relationship between environmental policies and innovation in three main respects: (i) while most recent studies adopt a microeconomic approach to examine the innovation-policy relationship, the present work examines this issue from a macroeconomic perspective, (ii) it takes the heterogeneity of countries' policies and technologies explicitly into account, and (iii) it examines the spillover effects on EI that may arise across countries through the trade channel[6].

In analogy with the knowledge and innovation literature (Griliches, 1979), spillovers were often in the basket of 'unmeasured influences on the accumulated level of knowledge'. This

[3] As Eberhardt and Tiel (2013, p.12) note: "panel time series methods allow for parameter heterogeneity across countries, which, as discussed above, is a central interest in our analysis. Third, panel time series methods can address the problems arising from cross-section correlation. Whether this is the result of common economic shocks or local spillover effects, cross-section correlation can potentially induce serious bias in the estimates because the impact assigned to an observed covariate in reality confounds its impact with that of the unobserved processes".

[4] Captured and explained by parameters, slopes, error terms.

[5] Eberhardt M. Helmers C. Strauss H. (2013) Do Spillovers matter when estimating private returns to R&D?, The Review of Economics and Statistics, 95.

[6] As Eberhardt and Tiel (2013) note: "The nature of macroeconomic variables in a globalized world, where economies are strongly connected to each other and latent forces drive all of the outcomes, provides a conceptual justification for the pervasive character of unobserved common factors." (p.9).

spillover effect can be considered a potential unobserved heterogeneity in models that only consider national policy effects[7].

This paper is related to the literature that analysis international spillovers, innovation and policies, which has largely taken a sector specific approach. Among other works, we quote here four relevant papers that touch on those issues. Verdolini and Bosetti (2017) study on the power sector shows that "whether domestic environmental policies affect the inward technology transfer of cleaner innovation from abroad. [..] Using data on cross-country patent applications, we provide evidence that environmental policy contributes to attracting foreign cleaner technology options to OECD markets but not to non-OECD markets". They show that this is due to the nature of the implemented policy instruments. Galeotti and Verdolini (2011) also focused on energy technologies and their supply and demand determinants: using a sample of 38 innovating countries they study how knowledge related to energy-efficient and environmentally friendly technologies flows across geographical and technological space. They demonstrate that higher geographical and technological distances are associated with lower probabilities of knowledge flow.

Along similar directions, but more focused on foreign investments dynamics, Dechezleprêtre et al. (2015) again focus on a specific sector (automotive) and study "the impact of environmental regulation on the international diffusion of new technology through the patent system" They conclude that by employing "a dataset of automobile emission standards between 1992 and 2007 and corresponding data on cross-border patent inflows of technologies developed to comply with these standards. Our analysis, based on a research design of country pair years, shows it is "regulatory distance" between countries rather than absolute regulatory stringency per se that matters for cross-border patent inflows: the flow of compliance technologies rises when regulatory standards in the inventor and the recipient countries become "closer". Finally, Perkins and Neumayer (2012) focus on international spillovers, CO2 efficiency and FDIs, claiming that "whether the strength of cross-border CO 2-efficiency spatial dependence working through import ties and inward foreign direct investment (FDI) stocks is greater in (a) countries with lower existing levels of domestic CO 2-efficiency and (b) countries with greater social capabilities in terms of a better educated workforce and higher institutional quality. We find that less CO 2-efficient countries and countries with higher institutional quality experience stronger FDI-weighted CO 2-efficiency spillover".

The paper provides new knowledge by using a flexible and broad macroeconomic setting that ground but tries to advance from seminal works on induced innovation effects in the energy-environmental framework (Popp, 2002). It complements recent papers that examine 'directed technological change' by observing clean technologies and policies with a focus on micro and sector based evidence. Among seminal papers, Acemoglu et al. (2016) analyse the transition to a decarbonised economy through technology and estimate the model by using firm level US energy sector data; their focus is on the role of carbon taxes and subsidies to stimulate a transition. Aghion et al. (2016) complement that analysis and provide evidence on the automotive industry sector, finding signs of path dependency in clean technological innovations, but also significant fuel tax effects. Other recent works examine specific policy realms, such as the EU emission trading (Martin et al. 2014a, Calel and Dechelezpretre, 2016); carbon taxes effects on manufacturing sector innovation (Martin et al.2014b) or specific environmental realms such as given renewable energy (Kim et al. 2017). The rationale of those type of studies is to deeply analyse specific policy effects on diversified clean technologies.

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[7] Accounting for observed and unobserved heterogeneity, including the role of spillovers, is a relevant pillar of the empirical literature around innovation drivers and effects (Eberhardt et al. 2013; Ertur and Musolesi, 2016). As example, the cited work by Eberhardt et al. (2013) finds that own-R&D becomes statistically insignificant when knowledge spillovers and common shocks are included.

Firm-based and sector based studies have thus prevailed in the literature, which has extensively made use of refined microeconomic econometric techniques aimed at assessing policy effects by comparing innovation in firms subject to policies and control groups. Recent Macroeconomic analyses take a rather specific perspective in assessing relationships between policies, renewable energy related patents and energy market competition (Nesta et al. 2014). Some of those macro panel analyses exploit techniques that were developed for micro datasets such as GMM.
The paper instead takes a broader macroeconomic and longer run perspective on green economy dynamics. It tries to add knowledge through the implementation of methodological novelties in the framework of green knowledge production functions (GKPF), or Green invention functions (Nesta et al. 2014, Popp, 2002) that use patents as best proxy of innovation at macroeconomic level, (Griliches, 1990), and maintains a policy-oriented objective.

The structure of the paper is as follows. Section 2 presents a literature review of works that adopt econometric models which aim at analysing individual heterogeneity. Section 3 presents the data. Section four shows preliminary results. Section 5 offers some conclusions.

2. Methods: Seemingly Unrelated Regression, individual effects, heterogeneous slopes

Seemingly Unrelated Regression Equations (SURE) as proposed by Zellner (1962) is a multivariate regression model based on Gaussian distribution, commonly distinct regressions contain different independent variables and seem unrelated, but due to correlated response variables the regressions are only seemingly unrelated and possess important information about each other. SUR has been extensively used in econometric literature and also in Gaussian graphical models (Goldberger, 1991, Anderson et al., 2001, Richardson and Sprites, 2002)

With the increase in availability of data of longer time duration (for countries, regions and firms) the traditional panel literature has moved from micro panels to large panels which has bring forth the emphasis on the literature of cross-sectional dependence. Previously panel data literature used to assume independence in cross-sectional error terms, heterogeneity across elements were limited to unit-specific intercepts which were treated as either random or fixed, error specific dependence literature was limited to spatial panels. The correlation among error terms can result from spatial effects, exclusion of some common effects or due to synergy with the economic variables. Ignoring cross-sectional dependence can lead deceiving inference and sometimes inconsistent estimation depending upon the extent and on the origin of its generation and its correlation with the regressors (Phillips and Sul, 2003, Andrews, 2005, Sarafidis and Robertson, 2009). Using of traditional unit roots tests in data with cross-sectional dependence can lead to biasness (O'Connell, 1998)

The literature suggests, various ways to deal with cross-sectional dependence, which mostly depends on the size of cross-sectional unit (N) and time-series unit (T). When N is small and T is sufficiently large, one of the efficient ways to deal with cross-sectional dependence is by using SURE estimation technique. SURE, assumes factors which generates cross-sectional dependence are not correlated with the regressors. SURE, estimation can also be applied to obtain asymptotic efficiency when data has presence of cointegrating regressors, if the T component is sufficiently large with the N component being substantially small, efficiency of SURE method exists in both static and dynamic cases as put forward by Phillips and Hansen (1990), Park and Ogaki (1991), Park (1992), Moon (1999) & Mark et al. (2003)

Due to this uniqueness in SURE, recently there has been an increase in the usage of it in various sub-disciplines of economics including environment and energy economics. The introduction of SURE in environmental economics can be attributed to List & Gallet (1999) in which they use US state level emission data of Sulphur dioxide and nitrogen oxide for suitableness of 'one size fits all' reduced-form regression method for EKC. They concluded that emissions at the US state-level follow an inverted-U shaped in accordance to previous literature. They also question the assumption of homogeneity in previous EKC literature, they derive to the conclusion that assuming homogeneity at cross-section level leads to miscalculation. Though their data had some measurement peculiarity but it can be treated as a cornerstone in EKC literature, which sets up the base for treating cross-sectional components heterogeneously in EKC literature. They allowed for both intercept and slope heterogeneity in their model in doing so they found their main concern was in which way to treat their response coefficients, i.e. either fixed or random. In doing so, they treat their model with SUR assuming the response coefficients as fixed and with Swamy estimator (Swamy, 1970) assuming randomness. They found Hausman (1978) test rejected randomness, so verifying the hypothesis that variable coefficients (state-specific intercept terms, i.e. of state income levels) were related to the location of EKC.

Recently usage of SURE and its applications in EKC have seen a lot of increase, some of the notable mentions are, Lee and Lee (2009), they use a dataset of 109 countries divided among seven regions covering 1971-2003 to quantify the causality among CO_2 emissions and real GDP using a Panel Seemingly Unrelated Regression Augmented Dickey-Fuller (Panel SURADF) test, due to its efficiency in treatment of cross-sectional correlation, they find different orders of integration for different countries for their variables. Marin and Mazzanti (2010) uses a sectoral level data of Italian firms using National Accounting Matrix including Environmental Accounts (NAMEA) dataset for a period of 1990-2007 to configure the EKC and IPAT model. They concluded CO_2 emissions were not binding Kyoto targets but a decrease in SO_x and NO_x gas emissions. They use SURE framework to determine the heterogeneity across the manufacturing sector, since its greater efficiency over Fixed effects model. They derive heterogeneity among these sub-sectors and put forward the question for further research in regarding to sectoral level environmental innovation and trade relations. Wagner and Grabarczyk (2016) uses Seemingly Unrelated Cointegrating Polynomial Regression to redirect the focus of EKC from previous works, which lacked treatment of cross-sectional dependence. They use a dataset of six countries for a time span of 1870-2013 of CO_2 emissions, SO_x emissions and GDP per capita and concludes that group-wise pooling results were same as compared to country-by-country or SURE estimation results, but it reduced the number of estimated parameters by one-third, also fully pooled panel estimates derived poorer results. This research is a n extension of similar work by Wagner (2008, 2015) with similar datasets.

Brons et. al. (2008), use SURE with Cross Equation Restrictions approach to model price elasticity of gasoline demand, they used data from previous 43 primary studies on the same and use them to derive their conclusion. They concluded, that the demand for gasoline is not very elastic compared to its price, and they also found both in short and long run fuel efficiency, car mileage and to some extent car ownership effects the relationship in between gasoline price and its demand. They also inferred that in their work, type of data, time horizon, geographic location and functional form of the demand equation were important factors. Miljkovic et. al. (2016) uses SURE method to estimate demand for types of fossil fuels in the US for a time-span 1918-2013, they use Granger Causality test, Weak Exogeneity test and Directed Acyclic Graphs tests to determine endogeneity in between the variables and perform a SURE approach to solve endogeneity. They concluded fossil fuels have very limited level of swap among each other. They also concluded natural gas, oil and coal behaved more being independent rather than being substitutes. Also demand for fossil fuels were very much effected by external shocks but their income elasticities were normal. Vesterberg (2016) uses SURE framework to explain hourly and end-user specific income elasticity for electricity, using an appliance level electricity consumption at hourly level in Sweden of 389 households between 2005 and 2008. The work is extremely important in deriving consumption patterns and peak electricity demand, the results were that income elasticities were highest during hours of lighting and kitchen, but were not significant for space heating. For each 24 hours, in the sample a different equation was used to estimate income elasticity and then jointly estimated 24 equations jointly using SURE framework.

Using a dataset of 57 developing countries over a time-span of four-time span, Wolfersberger et. al. (2015) concludes the linkage between long-term deforestation and economic development and institutions are at significant level, but over time in developmental stage of the country agriculture and forest do not always compete with one another regarding usage of land. They use a dynamic panel SURE model along with switching regression model to arrive to their results. In their analysis, they use a dynamic switching seemingly unrelated regression model, first use a probit model to explain the switchover in the phase of forest cover cycle in the country, and then they explain the land-usage share in between these two phases of forest levels. Chakir and Gallo (2013) used SUR Feasible Generalized Least Square- Spatial Autoregressive model- Random Effects (SUR-FGLS-SAR-RE) to predict future land use patterns in France using a dataset of 1992-2003 land use patterns and employing cross-sectional observations by Départment (French equivalent to NUTS3 region)

In order to test for causality in between radiative forcing and temperature using a multivariate time series data, Stern and Kaufman (2014) use SURE by imposing some restrictions. They use Schwert criterion (Schwarz Bayesian Information Criterion, Schwarz, 1978) to determine maximal lag length of VAR models. In their study, they employ a dataset of range from 1850-2011 to conclude that temperature change can be attributed to both natural and anthropogenic reasons, they also conclude temperature cause of greenhouse gas concentration, but the effects of greenhouse gasses and volcanic eruptions were mostly flexible depending upon the choice of model. They were unable to conclude about the effect of black carbon on temperature and they found the very weak effect of solar irradiance. Also regarding anthropogenic sulphate aerosols they concluded that their effect is only around half that is usually associated with them.

Wang et. al (2017) used an alternative bootstrap Granger causality test to appropriate the contemporaneous correlation of the error term in Vector Autoregressive Model which is based on SUR estimation., to establish the causality in between electricity consumption and economic growth in China. Using quarterly data from 1992 to 2016 they establish strong Granger causality relationship from gross domestic product to electricity consumption but weak in opposite sense. They use Bootstrap SUR Granger Causality test, due to the fact that in VAR system SUR estimator reduces to a single-equation Ordinary Least Square Estimator (OLS) as also stated by Kruskal (1968).

Hsu et. al. (2008) uses Panel Seemingly Unrelated Regression Augmented Dickey-Fuller (Panel SURADF) to study shocks to energy consumption of 84 countries of five different regions for a time period of 1971-2003. They conclude that difference in regions tends to influence the stationarity of energy consumption. They emphasis on the use of Panel SURADF, because of its power to determine cross-sectional effects and to determine members containing unit roots within a specific group.

Sardorsky (2009) uses SURE framework to determine linkages in Renewable energy consumption, CO_2 emissions and oil prices among G7 countries for a time period 1980-2005 timeframe, the paper concludes real GDP per capita and CO_2 per capita drives usage of per capita renewable energy consumption. The result also indicated negative impact of oil prices on renewable energy consumption.

Using panel data of 8600 Irish manufacturing firms Hyland and Steinbuks (2016) for a time period of 2004-2009 find compelling disparity of capital responsiveness and degree of variation in fuel prices which constituted different kinds of fuel. They use a SUR framework to estimate continuous stock of capital for different kinds of fuel.
Along with many various different regression estimation techniques Miller and Vela (2013) uses SURE framework to determine the effectiveness of environment related taxes (ERT) on pollution abatement performances of 50 countries for a time period of 1995-2008. They deduce the result that countries with higher ERT revenue have decreased their CO_2 and PM_{10} emissions and also have increased their renewable energy consumption.
Rosenman and Wolfe (2014) uses SURE framework to analyze the causality in between oil and gas markets using high-frequency data, they conclude with bi-directional causality effects among the commodities, they conclude that due to shortage and inventory surplus, this causality can extend on future contracts lasting six month or more.

3. The data

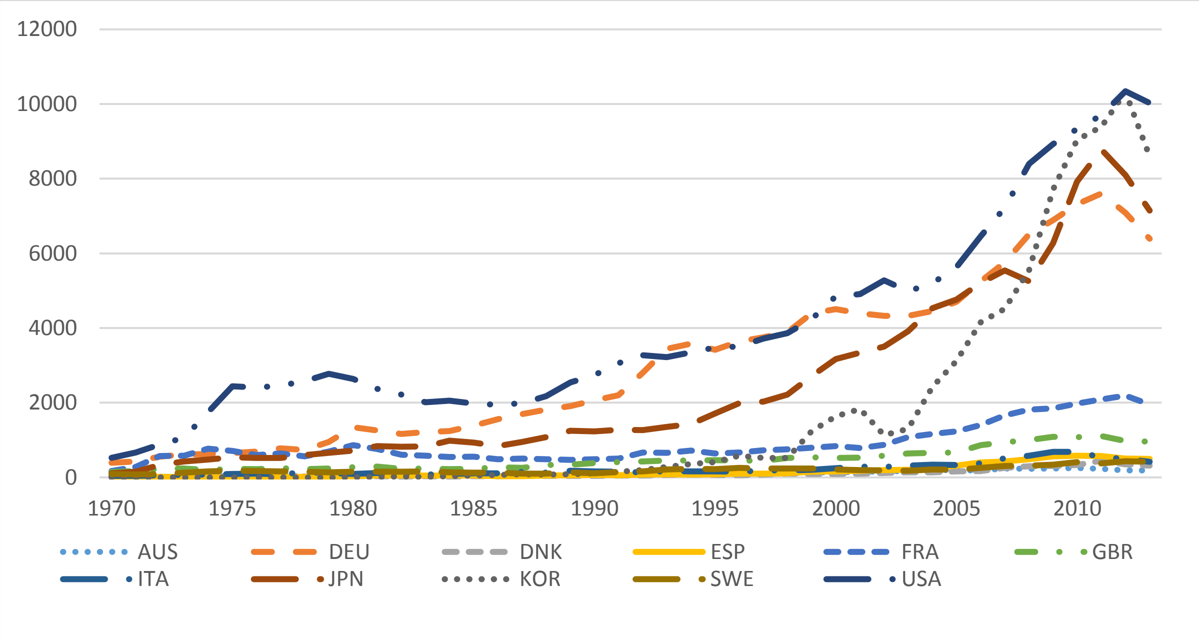
The empirical aim was to cover a sufficiently long period of time for a relevant set of high income countries in the OECD area. OECD is very variegated as far as economic and environmental dynamics are concerned (Musolesi and Mazzanti, 2013; Vollenbergh et al. 2009). The long T in the panel framework is necessary to attempt accounting and estimating heterogeneous cross country effects as far as possible. The usual limit in estimating panel models that include heterogeneity for deterministic intercepts and individuals slopes is the size of the panel, namely a sufficiently long T for each unit (country).
The green patents data are collected from OECD-STATS database. We consider patents which comes under Selected Environment-related Technologies as defined by OECD (IPC: ENV_TECH) and granted at USPTO (United States Patent & Trademark Office), and calculate the number of patents country-wise according to the inventor(s)'s country(ies) of residence. Given that we do not address knowledge spillovers, patents of an agent belonging to country i but submitted to country j are accounted as i-related patents.
As far as explanatory variables are concerned, we use number of Total Patents, Business enterprise Expenditure on Research and Development (BERD), Gross domestic Expenditure on Research and Development (GERD), Human Capital (HC). Total patents are calculated in a similar way as of Green Patents, only this time in the technology domain we select Total number of patents for a country granted at the USPTO according to the inventor(s)'s country(ies) of residence. BERD and GERD flow values are collected from OECD-STATS database, which follows Frascati Manual, we only consider total data as source of funds and data are in 2010 Dollars - Constant prices and PPPs. Missing values are filled in similar way as of Coe and Helpman (2009), and then we calculate BERD and GERD stock values using perpetual inventory method as in Coe and Helpman (1995) assuming depreciation rate to be 0.05. HC values are collected from Penn World Table version 9.0.

Discrete based policy indexes are derived from OECD sources and used as key policy indicators[8]. For each policy domain (i.e., climate change, energy efficiency and air pollution) CC1, EE1, and AP1 are computed following the methodology proposed in Nesta et al. (2014); six dummy variables were computed for policies which take the value 1 if the policy was in force in a certain year and in the country and 0 otherwise. The final index ranges from 0 (no regulations) to 6 (all instruments implemented) and is created as the sum of all the policies in

[8] We exploit OECD datasets being aware of the existence of OECD own policy stringency indicators, such as EPS. Our own constructed indicators of policy commitments are longer in time, given the empirical necessity to extend T in order to implement models that allow pretty complex heterogeneity oriented estimations.

force in a given year and in a given sector and country. CC2, EE2 and AP2 also account for persistency of a policy: if a policy is in force in *t-1* the value of the index in *t* will account for its effect. Finally the indexes CC3, EE3 and AP3 also account for the relative commitment of a country with respect to the average commitment in the sample.
Unweighted and weighted policy indicators are tested; weighted indexes aim at giving substance to stringency features. The indicators cover three domains: air pollution, climate change, energy efficiency. Though somewhat correlated, those allow differentiating the type of policy effect on innovations[9].
Figures 1-2 and table 1 present evidence on trends and main information regarding the variables in use in the paper.

Figure 1. Trend of green patents in selected countries



[9] Through energy prices might be a sound alternative (Sato et al. 2015, Popp, 2002), the use of Environmental policy categories that capture how stringency evolves over time allows assessing threshold effects that highly characterise the dynamic efficiency effects of policies. Energy prices as a measure of stringency also capture market distortions related to the energy market, endowments of fossil fuels, etc. All factors that tend to slowly vary over time as well. Policy indicators also account for multi dimensionality and can be preferred to PACE, which presents strong endogeneity issues (Kozluk and Zipperer, 2014; Morales Lage et al. 2016).

Figure 2. Average R&D expenditure, Human capital and Trade openness for selected countries

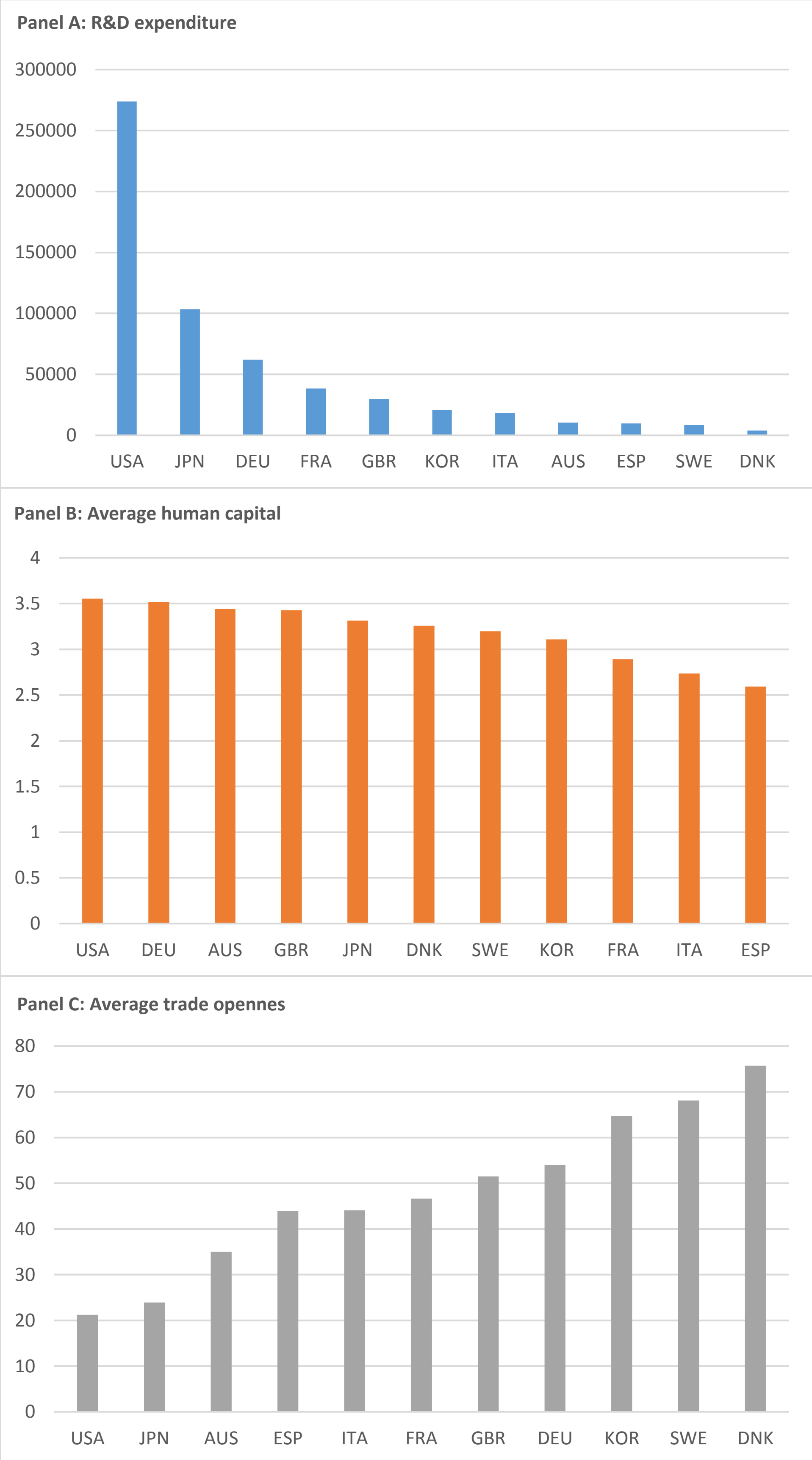


Table 1 - Descriptive stats

Variable	Description	Mean	min	max
lgreen	Green patents (log)	5.32	-6.93	9.24
lrd	R&D (log)	9.60	7.12	12.86
lhum	Human capital (log)	1.14	0.81	1.31
ltrade	Trade openness	9.60	2.20	5.85
CC1	Climate change policy indicator 1	1.41	0	5
CC2	Climate change policy indicator 2	3.38	0	21
CC3	Climate change policy indicator 3	6.51	0	42
EE1	Energy efficiency policy indicator 1	1.13	0	5
EE2	Energy efficiency policy indicator 2	2.85	0	21
EE3	Energy efficiency policy indicator 3	5.50	0	42

Note: *l* denotes logarithms; policy indicators are categorical variables

4. Econometric Analyses: investigating latent heterogeneity behind innovation – policy relationships

4.1 Two ways fixed effect models: deterministic heterogeneity by intercepts

Fixed effect models are a preferred route of estimation when the sample presents specific effects (regions, countries). It is always consistent and the efficiency gap with respect to random effect models vanishes as TxN increases.
Tests show that the inclusion of time dummies is statistically significant. We do take this specification as benchmark. We do estimate both models that include two knowledge inputs, R&D and human capital (as in Charlot et al. 2015) and more parsimonious models with R&D as patent input only.

First, the baseline specification that includes R&D, human capital and trade openness show all covariates (taken in logs) exposing positive and significant coefficients. Both fixed effects and time dummies are relevant according to F tests. We maintain this specification throughout notwithstanding its lower efficiency. Human capital is relatively more relevant looking at coefficient size, while statistical significance is equal.
The specification with R&D only (parsimonious innovation function) shows an increase in the R&D effect, and a decrease of trade openness below 10% significance (this is due to the presence of time dummies that are evidently related to trade dynamics). When the number of non-green patents is also included as covariate, it is significant and R&D slightly decreases its effect.

The next step is the inclusion of policy indicators. We test 9 indicators: three related to climate change, three to energy efficiency and three to air pollution. A description of these indexes is provided in section 3.

Concerning climate change related indicators, results are pretty robust across specifications. The baseline indicator CC1 is showing a negative coefficient in the regressions, while CC2 and

CC3 instead present positive and significant coefficients that are robust to the inclusion of different set of covariates in the innovation function. The difference in the magnitude of the effects of the three indicator might relate to their computation. In fact, while the baseline index, CC1 is a simple sum of policy instrument in a given year, the other two accounts also for the persistence of policy through time (i.e., a new policy sums up to the existing ones) and for the relative “distance” of a country’s policy regime from the mean value of the sample (i.e, if the policy index is above or below the median value).

Energy efficiency indicators alternatively present negative or insignificant coefficients. The result is more dependent on the inclusion of different covariates.

Air pollution policy indicators finally show lack of significance across the various specifications.

Regressions that set as dependent variable the ratio between green and non-green patents are also checked. R&D and human capital remain pillars in baseline specifications. The same is not true for trade openness.
When including CC-related policy indicators, the baseline CC indicator is positive and significant in this case, while alternate significance is shown for the other two, though they keep positive effects when statistically significant.

EE-indicators show similar and enhanced features. As far as the effect on the ratio of green/non green patents is concerned, the effect is always positive and mostly statistically significant across regressions.

Table 2. Fixed effect model without policy index

VARIABLES	(1) lgreen	(2) lgreen
lhum	8.304***	
	(0.612)	
lrd	0.910***	1.204***
	(0.0558)	(0.0602)
ltrade	0.345***	0.301**
	(0.126)	(0.148)
Constant	-13.37***	-7.088***
	(0.785)	(0.742)
Observations	544	544
R-squared	0.916	0.885
Number of code	16	16
F	149.5	108.3

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3. Fixed effect model including climate change policy index

VARIABLES	(1) lgreen	(2) lgreen	(3) lgreen	(4) lgreen	(5) lgreen	(6) lgreen
lhum	8.355***		8.623***		8.587***	
	(0.617)		(0.613)		(0.612)	
lrd	0.903***	1.196***	0.932***	1.229***	0.932***	1.230***
	(0.0562)	(0.0613)	(0.0560)	(0.0620)	(0.0559)	(0.0618)
ltrade	0.336**	0.261	0.335**	0.292*	0.330**	0.284*
	(0.140)	(0.166)	(0.138)	(0.165)	(0.138)	(0.165)
CC1	-0.0383**	-0.0517***				
	(0.0168)	(0.0198)				
CC2			0.0128***	0.00850**		
			(0.00359)	(0.00427)		
CC3					0.00685***	0.00506**
					(0.00189)	(0.00226)
Constant	-13.25***	-6.844***	-13.85***	-7.307***	-13.79***	-7.292***
	(0.830)	(0.806)	(0.812)	(0.795)	(0.810)	(0.794)
Observations	510	510	510	510	510	510
R-squared	0.917	0.884	0.918	0.883	0.918	0.883
Number of code	15	15	15	15	15	15
F	136.7	96.90	139.1	96.23	139.2	96.48

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4. Fixed effect model including energy efficiency policy index

VARIABLES	(1) lgreen	(2) lgreen	(3) lgreen	(4) lgreen	(5) lgreen	(6) lgreen
lhum	8.614***		8.437***		8.464***	
	(0.624)		(0.618)		(0.620)	
lrd	0.907***	1.210***	0.911***	1.211***	0.911***	1.210***
	(0.0562)	(0.0615)	(0.0563)	(0.0614)	(0.0564)	(0.0616)
ltrade	0.387***	0.325**	0.349**	0.290*	0.363**	0.319*
	(0.139)	(0.165)	(0.141)	(0.167)	(0.141)	(0.168)
EE1	-0.0453*	0.00481				
	(0.0242)	(0.0284)				
EE2			-0.00852	-0.00857		
			(0.00575)	(0.00681)		
EE3					-0.00260	-0.000764
					(0.00288)	(0.00341)
Constant	-13.73***	-7.237***	-13.47***	-7.098***	-13.55***	-7.215***
	(0.820)	(0.798)	(0.824)	(0.804)	(0.822)	(0.804)
Observations	510	510	510	510	510	510
R-squared	0.917	0.882	0.916	0.882	0.916	0.882
Number of code	15	15	15	15	15	15
F	136.1	95.30	135.7	95.67	135.3	95.31

Standard errors in parentheses; *** p<0.01, ** p<0.05, * p<0.1

Table 5. Fixed effect model including air pollution policy index

VARIABLES	(1) lgreen	(2) lgreen	(3) lgreen	(4) lgreen	(5) lgreen	(6) lgreen
lhum	8.442***		8.458***		8.459***	
	(0.619)		(0.624)		(0.621)	
lrd	0.905***	1.205***	0.909***	1.213***	0.908***	1.212***
	(0.0566)	(0.0617)	(0.0566)	(0.0615)	(0.0566)	(0.0616)
ltrade	0.394***	0.334**	0.389***	0.300*	0.392***	0.313*
	(0.140)	(0.166)	(0.141)	(0.166)	(0.141)	(0.167)
AP1	-0.0242	-0.0221				
	(0.0231)	(0.0273)				
AP2			0.00114	-0.00614		
			(0.00436)	(0.00511)		
AP3					0.000961	-0.00151
					(0.00224)	(0.00264)
Constant	-13.60***	-7.230***	-13.63***	-7.155***	-13.64***	-7.204***
	(0.819)	(0.798)	(0.828)	(0.800)	(0.825)	(0.800)
Observations	510	510	510	510	510	510
R-squared	0.916	0.882	0.916	0.882	0.916	0.882
Number of code	15	15	15	15	15	15
F	135.4	95.45	135.0	95.64	135.1	95.37

4.2 SURE models: towards heterogeneous slopes taking serial correlations into account

SUR models are not parsimonious in terms of degrees of freedom but the – oppositely to OLS - allow introducing a studying a full set of individual heterogeneity[10]. As fixed effect models, they show consistency properties and their efficiency is higher than FE but lower, at least for T≠∞, compared to models with enhanced poolability features.

9 countries are includable given the current time horizon of the dataset (32 years). To further save degrees of freedom, we stick to specifications where R&D, trade openness and environmental policies are the 3 covariates in the function, in addition to other fixed effects. Comments below and tables refer to SUR regressions that include Australia, Denmark, Italy, France, UK, USA, Germany, Spain, and South Korea[11]. The set of countries represent significant heterogeneity regarding economic, institutional, policy conditions. It is thus a relevant setting for applying SUR models.
We first present evidence for the unconstrained SURE that convey information on heterogeneous coefficients slopes. The set of baseline specifications without policies and then with climate change and energy efficiency policy indexes are tested.

First, the Breusch Pagan test strongly rejects the null hypothesis of independence (chi2(36) = 139.77). The country regressions are related. R&D expenditures are significant in all 9 countries, with the expected positive sign. As far as trade openness is concerned, the coefficient is generally positive and significant, expect for Germany where it is negative and significant. We do observe cases where does not impact on green patenting, such as Australia and United Kingdom (Table 2).

The inclusion of the first climate change baseline indicator (CC1) does not affect the R&D and trade effects. The coefficient is positive and significant for all countries but Australia, Germany, UK and South Korea. CC2 shows a slight different effect: its coefficient is positive and significant for USA, Spain and France, while it assumes a negative and significant effect for Australia.CC3 is related to a similar estimation outline.

Regarding energy efficiency related policy indicators (EE1), the baseline indicator shows a positive and significant effect except for Australia, Germany and Sweden where it is not statistically significant.
EE2 is always linked to a significant positive coefficient, besides the cases of UK and Germany (not significant) an Australia (negative and significant).

Summing up, estimations on the set of 9 countries show as it was expected that country specific effects can be heterogeneous. Main insights are that (i) Australia green patenting performance is not highly impacted by policies
Table 6 below summarizes the environmental policy- green patenting relationships.

[10] "As pointed out by Hsiao (2003), if the true model is characterized by heterogeneous intercepts and slopes, estimating a model with individual intercepts but common slopes could produce the false inference that the estimated relation is curvilinear" (Musolesi and Mazzanti, 2013).
[11] Additional regressions (not shown here) have included either Japan, Norway, Sweden.

Table 6 - SURE estimations - policy effects[12]

	CC1	CC2	EE1	EE2
Australia	Not significant	Negative and significant	Not significant	Negative and significant
Germany	Not significant	Not significant	Not significant	Not significant
Spain	Positive and significant	Positive and significant	Positive and significant	Positive and significant
France	Positive and significant	Positive and significant	Positive and significant	Positive and significant
UK	Not significant	Not significant	Positive and significant	Not significant
Italy	Positive and significant	Not significant	Positive and significant	Positive and significant
South Korea	Not significant	Not significant	Positive and significant	Positive and significant
Sweden	Positive and significant	Not significant	Not significant	Positive and significant
USA	Positive and significant	Positive and significant	Positive and significant	Positive and significant

Given the country specific nature of SURE estimations, and the constraints posed by the degrees of freedom in any given TxN datasets, the possibility of estimating effects for alternative countries is always related to the exclusion of others.

The (chi-squared) test on the equality of slopes convey will be performed in order to eventually opt for constrained SURE, that present enhanced efficiency with respect to fixed effects.

4.3 Mean group and common factors models: unobserved heterogeneity and clusters

Mean group estimators firstly developed by Pesaran and Smith (1995) are also introduced to address heterogeneity. The procedure is a first step where N regressions are estimated, and then estimated coefficients are averaged across groups (Musolesi and Mazzanti, 2013). Heterogeneity is addressed by modelling the way unobserved heterogeneity factors are included.
Results show that human capital outweighs R&D in a baseline specification. Testing the effects of policies without human capital in a parsimonious regression, we note that the baseline climate change indicator is positively and significantly related to green patents, while CC2 and CC3 are not. Energy efficiency indicators are all significantly related to green patents. Trade openness is mostly significant and positive across regressions.

It is worth noting that the addition of countries linear trends and outlier weighted means shrinks the statistical significance of regressions. Given this evidence and the fact that MG models are empirically coherent with panel datasets where T=N (see examples of applications in Pesaran et al. 1999), we can preliminary conclude that SURE specifications outweigh those models in this specific attempt of taking into account of country heterogeneity with T being pretty larger than N. Common correlated effects (CCE) and their pooled versions (CCEP) that originate from MG theoretical frameworks will be tested. CCE estimators augment the regression equation with cross-section averages of the dependent and independent variables to account

[12] The full set of SURE estimations is presented in tables 7-10 in the appendix.

for the presence of unobserved common factors with heterogeneous impact, CCEP is a sort of standard fixed effect model augmented with terms that should capture unobserved heterogeneity (Eberhard and Teil, 2013). The burden in terms of estimated parameters could be high.

5. Conclusions

The paper presents a broad macroeconomic perspective towards the analysis of green innovation function, where the effects of R&D, human capital and environmental policy are analyzed taking fully into account country heterogeneity, driven by observed and unobserved factors and correlations. Various econometric models that deal with the poolability issue are considered to study a long panel for relevant OECD countries.
Economic theory and growth / development economics has underlined that countries might possess ‘technologies’ that differ from one another and over time. Institutional features, different labor-capital ratios and, core object of this paper, different policy commitments, can pose into question the assumption of parameter homogeneity in the relationship between innovation outputs and inputs. Within green innovation functions, environmental policies are a key factor that stimulate innovation and invention. Stemming from environmental policy theory. Taking into account of internal and external policies effects, and the possible transmission of induced technical change through trade and international factors is necessary.
To address the aforementioned issues from methodological and economic-policy relevant perspectives, the paper exploits panel data models that reduce poolability to increase the investigation of various observed and unobserved heterogeneity, being conscious of the modelling costs. Panel time series methods allow for parameter heterogeneity across countries, can address the problems arising from cross-section correlation.

Results show that heterogeneity and serial correlation matter. Though the constraints posed by the reduction of poolability are somewhat binding, strong heterogeneity emerges with respect to the effects of R&D, trade and environmental policies towards the generation of green patents. Individual ‘innovation function’ with idiosyncratic features and different ‘models’ or clusters are drawn out by the analysis. This signifies that parametric specifications that address cross section heterogeneity and time related factors might enhance both the statistical robustness of results and their specific policy relevance.

6. Appendix

Table 7- SUR estimation without policy effects

7.	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	lgreen_AUS	lgreen_DEU	lgreen_ESP	lgreen_FRA	lgreen_GBR	lgreen_ITA	lgreen_KOR	lgreen_DNK	lgreen_USA
lrd_AUS	-0.245								
	(0.314)								
ltrade_AUS	1.352								
	(0.906)								
CC1_AUS	0.0494								
	(0.0678)								
lrd_DEU		1.844***							
		(0.335)							
ltrade_DEU		-0.920**							
		(0.449)							
CC1_DEU		0.0416							
		(0.0622)							
lrd_ESP			0.599***						
			(0.181)						
ltrade_ESP			0.505**						
			(0.249)						
CC1_ESP			0.214***						
			(0.0746)						
lrd_FRA				-0.457					
				(0.329)					
ltrade_FRA				0.321					
				(0.383)					
CC1_FRA				0.131***					
				(0.0353)					
lrd_GBR					1.209*				
					(0.705)				
ltrade_GBR					0.0540				
					(0.533)				
CC1_GBR					-0.0114				
					(0.0468)				

lrd_ITA						0.665			
						(0.410)			
ltrade_ITA						0.0158			
						(0.564)			
CC1_ITA						0.0430			
						(0.0676)			
lrd_KOR							1.076***		
							(0.124)		
ltrade_KOR							1.683***		
							(0.297)		
CC1_KOR							0.392**		
							(0.185)		
lrd_DNK								3.238***	
								(0.658)	
lhcDNK								-21.67***	
								(5.685)	
CC1_DNK								0.0213	
								(0.0622)	
lrd_USA									-0.276
									(0.370)
ltrade_USA									1.151**
									(0.471)
CC1_USA									0.136
									(0.0836)
Constant	1.782	-8.546***	-2.888	9.985***	-6.483	-1.352	-11.48***	3.507	7.879**
	(3.244)	(2.985)	(1.809)	(3.696)	(7.043)	(5.182)	(1.038)	(3.034)	(3.668)
Observations	34	34	34	34	34	34	34	34	34
R-squared	0.109	0.351	0.857	0.077	0.106	0.189	0.901	0.590	0.283
chi2_bp	823.1	823.1	823.1	823.1	823.1	823.1	823.1	823.1	823.1

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8. SUR estimation including climate change policy

VARIABLES	(1) lgreen_AUS	(2) lgreen_DEU	(3) lgreen_ESP	(4) lgreen_FRA	(5) lgreen_GBR	(6) lgreen_ITA	(7) lgreen_JPN	(8) lgreen_SWE	(9) lgreen_USA
lrd_AUS	0.611**								
	(0.238)								
ltrade_AUS	-0.0304								
	(0.650)								
CC3_AUS	-0.0905***								
	(0.0153)								
lrd_DEU		2.600***							
		(0.484)							
ltrade_DEU		-0.934**							
		(0.449)							
CC3_DEU		-0.0823							
		(0.0524)							
lrd_ESP			0.772***						
			(0.100)						
ltrade_ESP			0.603***						
			(0.219)						
CC3_ESP			0.0329***						
			(0.00625)						
lrd_FRA				-1.509***					
				(0.492)					
ltrade_FRA				1.119*					
				(0.591)					
CC3_FRA				0.0749***					
				(0.0125)					
lrd_GBR					0.284				
					(0.535)				
ltrade_GBR					0.448				
					(0.698)				
CC3_GBR					0.0922*				
					(0.0529)				
lrd_ITA						0.975***			
						(0.305)			
ltrade_ITA						-0.190			
						(0.360)			

CC3_ITA						-			
lrd_JPN							0.957***		
							(0.359)		
ltrade_JPN							0.312		
							(0.321)		
CC3_JPN							-0.0365		
							(0.0508)		
lrd_SWE								-1.118***	
								(0.335)	
ltrade_SWE								1.496***	
								(0.458)	
CC3_SWE								-0.0145***	
								(0.00483)	
lrd_USA									0.0138
									(0.482)
ltrade_USA									1.036**
									(0.447)
CC3_USA									0.00268
									(0.0205)
Constant	-0.490	-16.66***	-4.529***	17.68***	1.405	-3.495	-4.281	8.971***	4.839
	(1.826)	(4.226)	(0.865)	(4.236)	(4.720)	(3.260)	(4.469)	(1.977)	(5.263)
Observations	34	34	34	34	34	34	34	34	34
R-squared	0.146	0.406	0.844	0.467	0.139	0.150	0.194	0.040	0.278
chi2_bp	795.5	795.5	795.5	795.5	795.5	795.5	795.5	795.5	795.5

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6. SUR model with energy efficiency policy index

VARIABLES	(1) lgreen_AUS	(2) lgreen_DEU	(3) lgreen_ESP	(4) lgreen_FRA	(5) lgreen_GBR	(6) lgreen_ITA	(7) lgreen_KOR	(8) lgreen_SWE	(9) lgreen_USA
lrd_AUS	0.823**								
	(0.328)								
ltrade_AUS	0.829								
	(0.758)								
EE2_AUS	-0.116***								
	(0.0316)								
lrd_DEU		2.545***							
		(0.352)							
ltrade_DEU		-0.165							
		(0.345)							
EE2_DEU		-0.164***							
		(0.0420)							
lrd_ESP			0.798***						
			(0.107)						
ltrade_ESP			0.378						
			(0.238)						
EE2_ESP			0.0209***						
			(0.00640)						
lrd_FRA				-0.329					
				(0.376)					
ltrade_FRA				-0.342					
				(0.429)					
EE2_FRA				0.0460**					
				(0.0227)					
lrd_GBR					2.423***				
					(0.578)				
ltrade_GBR					0.969				
					(0.707)				
EE2_GBR					-0.0922***				
					(0.0262)				
lrd_ITA						0.957**			
						(0.393)			
ltrade_ITA						0.224			
						(0.564)			

EE2_ITA						-0.0129			
						(0.0219)			
lrd_KOR							1.072***		
							(0.0821)		
ltrade_KOR							0.637***		
							(0.245)		
EE2_KOR							0.132***		
							(0.0365)		
lrd_SWE								-0.736**	
								(0.334)	
ltrade_SWE								0.443	
								(0.426)	
EE2_SWE								0.0200	
								(0.0268)	
lrd_USA									0.0840
									(0.331)
ltrade_USA									1.212***
									(0.433)
EE2_USA									-0.0107
									(0.0116)
Constant	-5.183**	-18.98***	-3.950***	11.27***	-22.30***	-4.785	-6.951***	9.832***	3.509
	(2.506)	(3.674)	(1.142)	(4.256)	(6.964)	(5.202)	(1.157)	(2.724)	(3.316)
Observations	34	34	34	34	34	34	34	34	34
R-squared	0.073	0.408	0.830	-0.000	0.106	0.123	0.900	-0.059	0.267

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 10 - SUR model including air pollution policy index

VARIABLES	(1) lgreen_AUS	(2) lgreen_DEU	(3) lgreen_ESP	(4) lgreen_FRA	(5) lgreen_GBR	(6) lgreen_ITA	(7) lgreen_JPN	(8) lgreen_SWE	(9) lgreen_USA
lrd_AUS	0.790**								
	(0.372)								
ltrade_AUS	0.960								
	(0.800)								
AP2_AUS	-0.0882***								
	(0.0301)								
lrd_DEU		2.662***							
		(0.331)							
ltrade_DEU		-0.488							
		(0.303)							
AP2_DEU		-0.121***							
		(0.0358)							
lrd_ESP			0.813***						
			(0.105)						
ltrade_ESP			0.146						
			(0.199)						
AP3_ESP			0.0188***						
			(0.00456)						
lrd_FRA				-0.0933					
				(0.409)					
ltrade_FRA				-0.617					
				(0.481)					
AP2_FRA				0.0485***					
				(0.0188)					
lrd_GBR					1.938***				
					(0.547)				
ltrade_GBR					0.123				
					(0.633)				
AP2_GBR					-0.0549*				
					(0.0307)				
lrd_ITA						1.256***			
						(0.385)			
ltrade_ITA						0.0233			
						(0.559)			

AP2_ITA						-0.0121			
						(0.0199)			
lrd_JPN							0.971***		
							(0.285)		
ltrade_JPN							0.00231		
							(0.181)		
AP2_JPN							-0.703		
							(0.688)		
							(0)		
lrd_SWE								-0.836***	
								(0.305)	
ltrade_SWE								0.117	
								(0.433)	
AP2_SWE								0.0497**	
								(0.0225)	
lrd_USA									0.313
									(0.403)
ltrade_USA									0.989**
									(0.463)
AP2_USA									-0.00551
									(0.00972)
Constant	-5.438*	-19.03***	-3.236***	9.830**	-14.12**	-6.951		11.94***	1.359
	(2.859)	(3.390)	(1.124)	(4.472)	(6.450)	(5.095)		(2.308)	(4.432)
Observations	34	34	34	34	34	34	34	34	34
R-squared	0.081	0.381	0.840	0.011	0.107	0.147	0.187	-0.023	0.283
chi2_bp	976.2	976.2	976.2	976.2	976.2	976.2	976.2	976.2	976.2

Standard errors in parentheses;*** p<0.01, ** p<0.05, * p<0.1

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