INNOVATION-FUELLED, SUSTAINABLE, INCLUSIVE GROWTH

Working Paper

Threshold Policy Effects and Directed Technical Change in Energy Innovation

Lionel Nesta
Université Côte d'Azur, CNRS, Gredeg, OFCE SciencesPo and SKEMA Business School, France

Elena Verdolini
FEEM and CMCC, Italy

Francesco Vona
OFCE SciencesPo, SKEMA Business School and Université Côte d'Azur (GREDEG)

11/2018 May

This project has received funding from the European Union Horizon 2020 Research and Innovation action under grant agreement No 649186

Threshold Policy Effects and Directed Technical Change in Energy Innovation*

Lionel Nesta† Elena Verdolini‡ Francesco Vona§

Abstract

This paper analyzes the effect of environmental policies on the direction of energy innovation across countries over the period 1990-2012. Our novelty is to use threshold regression models to allow for discontinuities in policy effectiveness depending on a country's relative competencies in renewable and fossil fuel technologies. We show that the dynamic incentives of environmental policies become effective just above the median level of relative competencies. In this critical second regime, market-based policies are moderately effective in promoting renewable innovation, while command-and-control policies depress fossil based innovation. Finally, market-based policies are more effective to consolidate a green comparative advantage in the last regime. We illustrate how our approach can be used for policy design in laggard countries.

Keywords: Directed technical change; threshold models; environmental policies; policy mix.

JEL classification: Q58, Q55, Q42, Q48, O34

*Lionel Nesta and Francesco Vona gratefully acknowledge the funding received from the H2020 project: 'Innovation-fuelled, Sustainable, Inclusive Growth (ISI-GROWTH)' under grant agreement 649186. Elena Verdolini gratefully acknowledges funding received funding from the European Union's Horizon 2020 research and innovation program under grant agreement No. 730403, Project INNOPATHS. The authors are grateful to David Popp and the participants of the CONCORDi 2017 Conference for their valuable comments. The usual disclaimer applies.

†Université Côte d'Azur, CNRS, Gredeg, OFCE SciencesPo and SKEMA Business School, France, lionel.nesta@unice.fr

‡FEEM and CMCC, Italy elena.verdolini@feem.it

§OFCE SciencesPo, SKEMA Business School and Université Côte d'Azur (GREDEG) francesco.vona@sciencespo.fr

1 Introduction

The Paris Agreement, signed in December 2015 by 195 parties, represents a global action plan to address climate change by limiting global warming to well below two degrees. One key feature of the Agreement, compared to the Kyoto Protocol, is that all countries committed to undertake an active role to reduce greenhouse gas (GHG) emissions, even if recognizing the principle of "common but differentiated responsibilities and respective capabilities". This important political turnaround reflects a more general shift in policy making, whereby fast-developing and developing countries are taking a more active role in addressing the challenges linked with sustainable development. With respect to climate change, stronger commitment arose from the fast growth in global share of GHG emissions from BRIICS countries in last two decades[1] and from growing concerns in developing and fast-developing countries over the consequences of climate change.

A crucial step in successfully curbing emissions is to promote innovation in green technologies. This opens up opportunities as well as burdens for both developing and fast-developing countries, and raises some key questions related to the design of effective climate policies. What is the optimal policy portfolio to redirect innovation towards low-carbon technologies? Are policy instruments equally effective in developed and developing countries? And, given the strong path dependency in innovation, how can emerging economies move from being laggards in low-carbon innovations to becoming leaders in this promising domain?

This paper proposes a new empirical methodology to provide a preliminary and necessarily incomplete answer to these questions, shedding light on the choice of the appropriate policy instrument to promote green innovation in countries at different stages of technological development. Using information on patent production and environmental policies, we test whether the dynamic incentives of different policy instruments exhibit discontinuities depending on the country's technological know-how. In this context, the factor mediating policy effectiveness is the level of relative technological specialization of a given country, which is measured by the ratio of the stock of patents in green versus brown energy technologies. This variable captures the path-dependency in the direction of energy innovation of a given country.

Detecting discontinuities in policy effectiveness is essential for identifying the environmental policies that are relevant at specific stages of technological development. To the best of our knowledge, the current empirical literature on the determinants of energy innovation and on directed technical change has ignored this issue.[2] The starting point of our paper is to see the inducement effect of environmental policies on the direction and the rate of innovation as a particular case within the more general debate on the theoretical relationship between optimal policy and the stage of technological develop-

[1] As of today, 2/5 of global GHG emissions comes from BRIICS: Brazil 2.3%; Russia 5%, but second after the USA in per-capita terms; China 26.8%, reflecting the boom of Chinese industrial production after the entry in the WTO in 1999; India 6.7% and South Africa 1.1%

[2] See for instance Popp (2002), Johnstone et al. (2010), Verdolini & Galeotti (2011), Nesta et al. (2014), Noailly & Smeets (2015), Aghion et al. (2016), Calel & Dechezleprêtre (2016).

ment (Acemoglu et al. 2006, Aghion & Howitt 2006). As suggested by Acemoglu et al. (2006), policies should be changed *at the right moment* to switch from an investment-based strategy for countries far from the technological frontier to an innovation-based strategy for countries near the frontier. Understanding whether and to what extent policy effectiveness depends on the stage of technological development would provide a much-needed foundation for clearer policy insights to emerging economies such as China and India. For these countries, which also face other development challenges, the choice of the most effective policy instrument is indeed a crucial concern.[3] Our research addresses this general issue using energy innovations as an important case study, given the potential opportunities and burdens opened by the Paris Agreement

To identify different regimes of policy effectiveness, we adapt Hansen's threshold effect model (Hansen 1999), which is particularly suited to empirically detect regime switches in the effect of a certain (policy) variable contingent on specific contextual factors, i.e. green vs. brown technological specialization. We amend the model in two ways. First, we use the pre-sample mean of the dependent variable to model unobservable individual effects in a flexible way (Blundell et al. 2002). This method is particularly useful in retrieving consistent estimates of variables that have minimal variation over time, such as environmental policies. Second, we test the presence of discontinuities in the effect of two different policy instruments. As discussed at length below, countries can adopt either market-based (i.e. subsidies and taxes) or command-and-control policies (i.e. emission standards) to address climate change mitigation. These policy instruments differ in effectiveness and in political acceptability, but also, and more importantly in our context, in dynamic incentives to innovate. Furthermore, we address the issue of environmental policies endogeneity through an IV strategy. The main concern in addressing endogeneity is not to retrieve a precise estimate of the effect of each policy, but rather to validate the thresholds of technological specialization around which the policy effect significantly changes using arguably exogenous variations in policy stringency.

Our main finding is that there exist two discontinuities in policy effectiveness depending on the in-house competencies in renewable relative to fossil fuel technologies. This suggests the presence of three policy regimes. In countries whose level of relative competencies is below the median, neither market-based nor command-and-control policies being effective in promoting greener technology options (first regime). As countries increase their specialization towards renewable innovation, the dynamic incentives of environmental policies become powerful. In this critical second regime, market-based policies are moderately effective in promoting green innnovation, while command-and-control policies play an important role in depressing brown innovation. Finally, only

[3] Our contribution specifically focuses on the dynamic incentives of domestic policies. Recent contributions in this literature have pointed to the role played by foreign (demand-pull) policies in promoting domestic innovation (Peters et al. 2012, Dechezleprêtre & Glachant 2014) or foreign patenting (Verdolini & Bosetti 2017). However, available evidence confirms that the role of foreign demand is significantly less strong that that of domestic demand and policies. In the case of wind, for instance, Dechezleprêtre & Glachant (2014) shows that the marginal impact of foreign demand is considerably lower – by a factor of 12 – that of domestic demand in a sample of OECD countries. In Section 5.1 we briefly return on this issue, describing the robustness of our results to the inclusion of proxies for foreign demand pull.

market-based policies are effective in the third policy regime, allowing to consolidate a comparative advantage in renewable energy technologies. These findings lead to a key policy implication: countries need to strengthen their level of green relative to brown technological competencies before they can fully benefit from the dynamic incentives of environmental policies.

The remainder of the paper is organized as follows. Section 2 contains a conceptual discussion on the importance of discontinuities in the effects of policies as contingent on technological competencies. Section 3 presents our empirical approach by detailing the modifications to Hansen's threshold model, describing our data and sources, and discussing the instrumental variables chosen to address the concerns related to the endogeneity of the policy variables. Sections 4 and 5 present and discuss our results, respectively. Section 6 concludes, highlighting the key policy implications of our analysis.

2 Discontinuous Policy Effects on Innovation

The idea that appropriate policy choice is contingent on the stage of technological development of a country is certainly not new in the literature on economic growth. Rodrik (2005) provides a thorough discussion of the appropriate growth strategy, defined as mix of policies and institutions, for countries at different stages of economic development. Several papers relate the emergence of multiple equilibria and poverty traps to factors, and thus implicitly to policies, affecting the accumulation of physical (see, e.g., Murphy et al. 1989) and human capital (see, e.g., Galor & Zeira 1993) as well as technological development (see, e.g., Howitt & Mayer-Foulkes 2005). This notwithstanding, only Acemoglu et al. (2006) develop an endogeneous growth model that explicitly examines how the choice of the appropriate policy depends on the distance to the technological frontier. In this model, laggard countries do not have enough competencies to innovate, but invest in order to enhance their capacity to absorb foreign innovations. At an early stage of development, entry barriers and anticompetitive strategies can favour technological catching-up because they magnify the appropriability of these investments in absorptive capacity. However, as countries approach the technological frontier, a switch in policy is required to jump to an innovation-based growth path, which entails greater competition and the continuous entry of newcomers to boost the emergence of new ideas. Importantly, the model exhibits discontinuities: countries that reach a certain threshold of competencies but do not switch to innovation-based policies remain stack into a non catching-up trap.

These policy threshold effects are extremely important when two technologies compete with one another, as in the case of green vs. brown innovations. Indeed, what matters in the context of competing technologies is not the overall level of competencies, but the existing comparative advantages in one technology versus the alternative. As pointed out by the seminal work of Arthur (1989), pure market forces may not ensure that the most socially desirable technology prevails. In the presence of increasing returns in technological adoption, small random variations in the initial number of adopters may lock the economic system into an inefficient, or less socially desirable, technology. The paradox is that although technological selection can occur through small random events, escaping the lock-in may become very costly because increasing returns in adoption are further reinforced by complementary investments in the dominant technology.

Acemoglu et al. (2012) study the path-dependency in green vs. brown innovation as function of environmental policies and of the ratio of the accumulated competencies. Their model shows that, provided that the degree of substitution between green and brown technologies is not too low, there always exists a policy stimulus that allows to switch on a greener innovation path and, at the same time, sustain long-term economic growth. Notably, the magnitude of the policy response required to redirect energy innovation depends on the relative technological maturity of brown and green technologies. As a result, the system can exhibit sharp nonlinearities in policy effectiveness as dependent on the relative degree of specialization in green *versus* brown technologies.

In practice, redirecting energy innovation is an enormous endeavor. The energy system is locked in fossil fuel technologies both because of accumulated learning and because of the support of an extensive infrastructure of fuel supply, distribution, maintenance and ancillary services (Kline 2001). Improving the efficiency of well-established fossil fuel technologies through more incremental changes (i.e. brown innovation) is presumably easier than investing in radical, yet uncertain innovation in renewable energy, which entails large fixed costs to learn and experiment (i.e. green innovation). In this respect, the transition from fossil fuel to renewable technologies can be seen as a case of locking-out. The energy system should gradually replace a well-established dominant technology with a new competing technology triggering a virtuous cycle whereby increased adoption gives rise to further technological developments. In this context, the possibility that a policy stimulus may be too small to trigger a virtuous circle of clean innovations is not a remote concern, but rather constitutes a central problem for policy design.

Surprisingly, while the issue of switching from a dominant technology to a new technology has been addressed from different theoretical perspectives, empirical research is scant on the role of policy in making a technological lock-out feasible. The main contribution of our paper is to present an empirical case study of how policies may contribute to lock out from a mature technology (fossil fuel) to a new technology (renewables). In doing so, our second contribution is to use a methodology, the threshold effect model developed by Hansen (1999), that allows to empirically identify discontuinities in policy effectiveness. We differ from earlier empirical tests based on the model of Acemoglu et al. (2012), which assume the effect of environmental policies as independent from the level of competencies in clean relative to dirty technologies (Aghion et al. 2016, Noailly & Smeets 2015). By explicitly allowing for the policy effectiveness to depend on the past competencies in green and dirty technologies, we relax and empirically test this assumption.

Our final contribution concerns the choice of the appropriate policy instrument in environmental economics. To spur environmental innovations, the choice of the appropriate policy is complicated by multidimensionality. We distinguish between policies that affect innovation directly and indirectly.

On the one hand, policies such as green public research and development (R&D) investments affect innovation directly and purposively aim at building technological competencies in a given domain. These investments represent an essential policy in building a critical level of competencies (Freeman 1982), but usually their effects emerge with a long time delay. In the case of energy innovation, Popp (2016) shows that research outputs from basic R&D projects appear after a time span of up to ten years. This is due to the fact that building competencies necessarily involved a wide variety of public and private institutions active in upstream research, namely public research organizations and private firms. But equating technological competencies with upstream research exclusively would downplay the role of downstream applications as a source of new ideas (Rosenberg 1982). Technological trajectories are the product of technology developers and final adopters, due to the multiple linkages that bond end-users with inventors (Kline & Rosenberg 1986). Whether technology-pushed or demand-pulled (Dosi 1982), innovations always involve the commitment of a great variety of actors. In these complex networks, government intervention is essential (Mazzucato 2015) not only in reducing the level of uncertainty born in research activities but also in providing markets with clear signals on where, when and how to invest.[4]

On the other hand, all those instruments which directly address environmental externalities also indirectly affect the incentives to invest in green innovations. Among these, economists generally distinguish between command-and-control (CC) and market-based (MB) approaches (Requate 2005). The most commonly used command-and-control instruments are standards regulating either the type of technology adopted or the level of emissions. Commonly adopted market-based instruments include subsidies on abatement of emissions, tradable permits, and to a lesser extent, emission taxes.

Economists' preference for MB instruments is by virtue of their static efficiency: MB instruments incentivize pollution reductions through either direct or indirect prices, leaving firms free to decide how much they want to emit or to abate. In a competitive market, such instruments lead to the equalization of marginal abatement costs for all actors in the market, meaning that a given emission target is reached at the lowest possible cost. However, as shown by the seminal paper by Weitzman (1974), this conclusion is sensitive to the way of abatement costs and benefits are designed: price-based policies outperform quantity-based policies only when uncertainty regarding abatement costs is relatively low and when technological alternatives are relatively abundant.[5] Further, the superior performance of MB instruments over CC instruments is not warranted if one either relaxes the assumption of perfectly competitive markets or considers the dynamic incentives to innovation associated with each policy (Requate 2005). Empirically, a growing literature on the determinants of renewable energy innovations did not reach a firm conclusion on the superiority of one instrument over the other (Johnstone et al.

[4]For the case of green technologies, Mazzucato (2015) provides evidence on the crucial role of federally funded R&D research labs for the development of green start-ups. Vona et al. (2017) show that the presence of these public research laboratories and of green inventors favour the emergence of green industrial clusters in US regions.

[5]Extensions of the Weitzman's model that incorporate technology choices are carried out in a static framework and therefore did not allow for path dependency in innovation, i.e., the influence of past competencies on the probability of innovating (e.g., Krysiak 2008).

2010, Nicolli & Vona 2016). Using the long history on environmental policies of the USA, two papers examined the effect of a change in policy strategy. Popp (2003) shows that after the passage of the 1990 CAAAs, which instituted permit trading, innovation activity decreased in intensity. However, he also shows that the inventions developed under the market-based policy were of higher efficiency than those developed under the command-and-control regulation. Taylor (2012) shows that for both the US cap-and-trade program for SO_2 emissions and the Ozone Transport Commission NO_x Budget Program, patenting activity collapsed when traditional CC regulation was replaced by a cap-and-trade program (MB). A likely explanation put forward in the analysis is that planned investments in clean technologies, which are spurred by the expectation of high permit prices, are reduced once the economic actors realize that the regulation may not be as stringent as expected. Another explanation is that either MB or CC policies can be appropriate at a different stage of technological development.

To deal with policy multidimensionality, our working assumption is that any policy indirectly affecting innovation rests upon a critical accumulation of scientific and technical knowledge. To paraphrase Patel & Pavitt (1997), if a country wants to innovate in solar energy, it must know about photovoltaic science; if a country wants to specialize into wind turbines, it must know about wind gust modeling and aerodynamics. Hence, the very step for a country is to invest in knowledge accumulation in order to build its critical mass, thereby increasing its absorptive capacity (Cohen & Levinthal 1989) and develop its own expertise in particular fields of applications. Only then will the dynamic incentives of CC and MB instruments come into play. Our empirical strategy allows to directly explore the possibility that the appropriate choices between CC and MB depends on a country's stage of technological development. Indeed, lacking a clear theoretical ranking of instruments as explained above, testing this hypothesis ultimately remains an empirical issue.

3 Empirical Framework

3.1 Econometric Strategy

The starting point of our analysis is the standard empirical specification to test the effect of policy on the direction of technical change in the energy sector (Aghion et al. 2016, Noailly & Smeets 2015). This model reads as:

$$y_{i,t} = \beta_{mb}MB_{it} + \beta_{cc}CC_{it} + \beta_K K_{R/F,it} + \mathbf{BX} + \mu_i + \lambda_t + e_{it}, \qquad (1)$$

where innovation y and knowledge stock $K_{R/F}$ are the log-transformed ratio of innovation (resp. knowledge stock) in green innovation over the innovation (resp. knowledge stock) in brownl technologies. This is consistent with the literature on directed technical change. Variables MB and CC stand for market-based and command-and-control policies, respectively, while $\mathbf{X}$ is a vector of control variables that will be specified in the next Section; μ_i and λ_t are country i and time t effects; and e_{it} is the error term. The parameters of interest are β_{mb} and β_{cc}, which are the effects of the two types of policies on renewable energy innovation, which we expect to be significant and positive.

Our key novelty is that policy effectiveness depends upon the degree of specialization in renewable energy. The most immediate econometric counterpart is to extend specification 1 by interacting the two policy variables MB and CC with the ratio of the two knowledge stocks ratio $K_{R/F}$. The basic model then becomes:

$$\begin{aligned} y_{i,t} = & \beta_{mb} MB_{it} + \beta_{cc} CC_{it} + \beta_K K_{R/F,it} + \\ & \beta_{mbK} K_{R/F,it} \times MB_{it} + \beta_{ccK} K_{R/F,it} \times CC_{it} + \\ & \mathbf{BX} + \mu_i + \lambda_t + e_{it}. \end{aligned} \tag{2}$$

A limit of Equation 2 is that it assumes that the change in the policy effectiveness on innovation is linear in K. That is: $\partial y_{it}/\partial pol = \beta_{pol} + \beta_{polK} \times K_{R/F,it}$, where pol stands for either MB or CC policies. One alternative is to investigate whether there are discontinuities in this interaction, so that there may be threshold values of $K_{R/F}$ below which a given policy is ineffective and above which the policy becomes both effective and stable.

To detect sharp nonlinearities in the effect of policies on green innovation, we rely on the estimation and inference methodology developed by Hansen (1999). We amend Hansen's approach in two ways. First, we model the country fixed effect μ_i using the pre-sample mean of the dependent variable rather the relying on within-country variations. Our motivation lies in the fact that although there is a time variation in the policy variables, such measures change only slowly over time. As is well known in the literature (Blundell et al. 2002), the use of within differences would withdraw a large share of the identifying variation, possibly leading to inconsistent estimates of the parameters of interest β_{mb} and β_{cc}.[6] Second, whereas in his example on firm financial constraints Hansen (1999) interacts the threshold variable with only one variable of interest – namely cash flow – we interact the threshold variable – namely the ratio between the renewable and the fossil fuel knowledge stock K– with two variables of interest, MB and CC policies. This approach allows us to test which policy approach is more effective at a given level of technological maturity and thus to track how the appropriate policy mix changes with the level of technological competencies.

Hansen's method also determines empirically the number of thresholds underlying the relationship between the dependent variable and the variable(s) of interest. For the case of two policy instruments and one threshold, the model reads:

[6] One objection against the use of the pre-sample mean is that the presence of less developed countries in our sample may substantially decrease its variance. Should this be the case, one would not be able to properly account for unobserved heterogeneity among less developed countries. We test this by first assuming that the pre-sample mean follows a normal distribution $PSM \sim N(\mu, \sigma)$. We then condition parameters μ and σ on the log of GDP per capita using maximum likelihood estimation methods. Results show that whereas μ is positively associated with GDP per capita, the variance of the distribution captured by parameter σ is independent from the level of development of the country, implying that the country fixed effects can be accounted for using the pre-sample mean. Results are available upon request.

$$\begin{aligned} y_{i,t} =&\beta_{mb_1}(\gamma)MB_{it}\mathbf{I}(K_{R/F,it} \leq \gamma) + \beta_{p_2}(\gamma)MB_{it}\mathbf{I}(K_{R/F,it} > \gamma)+ \\ &\beta_{cc_1}(\gamma)CC_{it}\mathbf{I}(K_{R/F,it} \leq \gamma) + \beta_{cc_2}(\gamma)CC_{it}\mathbf{I}(K_{R/F,it} > \gamma)+ \\ &\beta_K K_{R/F,it} + \mathbf{BX} + \mu_i + \lambda_t + e_{it}, \end{aligned} \tag{3}$$

where $\mathbf{I}$ is an indicator variable set to unity, whether the threshold variable $K_{R/F,it}$ is below ($K_{R/F,it} \leq \gamma$) or exceeds ($K_{R/F,it} > \gamma$) a given threshold value γ. An important requirement is that the panel is balanced with n countries and T time periods, so that $N = n \times T$. Notice that this model allows for the *empirical* detection of discontinuities in the relationship between the threshold variable $K_{R/F}$ and our variables of interest. It is thus important to compare the results of this model with those of the interactions model in (2), as we do extensively in the next Section.

To retrieve an estimate of γ, we should first define $\mathbf{Y}$, the vector stacking all observations of the dependent variable; $\hat{\mathbf{Y}}(\gamma)$, the corresponding vector of predicted values by estimating equation 3; and the vector of residuals $\hat{\mathbf{e}}(\gamma) = \mathbf{Y} - \hat{\mathbf{Y}}(\gamma)$. The algorithm proposed by Hansen (1999) chooses γ so as to minimizes the sum of squared errors $S_1(\gamma)$, where $S_1(\gamma) = \hat{\mathbf{e}}(\gamma)'\hat{\mathbf{e}}(\gamma)$. More precisely, the estimator of $\hat{\gamma}$ reads:

$$\hat{\gamma} = \underset{\gamma}{\operatorname{argmin}}\ S_1(\gamma). \tag{4}$$

The computation of the least squares estimate of the threshold γ involves the minimization exercise 4. To do so, we first sort the threshold variable $K_{R/F}$ in ascending order and exclude the bottom and top 5% of observations. This step is to rule out regimes which would include too few observations below or above an obtained threshold. The remaining $N_{.05}^{.95}$ observations represent the set of values over which the optimal $\hat{\gamma}$ is determined. We obtain the sum of squared errors $\hat{\mathbf{e}}(\gamma)$ and its associated $S_1(\gamma)$ using equation in (3). The smallest value for $S_1(\gamma)$ is $\hat{\gamma}$.

The first step regards the significance of the threshold and tests whether the identified regimes are significantly different from one another, the null hypothesis being $H_0 : \beta_1 = \beta_2$, where 1 and 2 refer to the estimated coefficients in the first and second regime, respectively. The second step concerns efficiency in order to determine the 95% confidence interval of the threshold likely values, with the null hypothesis being $H_0 : \hat{\gamma} = \gamma^*$, the *true* value of the threshold. Appendix A provides more details on the inference procedure.

Model (3) implicitly assumes that there are only two regimes of policy effectiveness in the direction of technical change. Yet, there may very well be several thresholds. For instance, in the case of two policy instruments and two thresholds, with $\gamma_1 < \gamma_2$, the equation becomes:

$$
\begin{aligned}
y_{i,t} =& \beta_{mb_1}(\gamma) MB_{it}\mathbf{I}(K_{R/F,it} \leq \gamma_1) + \beta_{mb_2}(\gamma) MB_{it}\mathbf{I}(\gamma_1 < K_{R/F,it} \leq \gamma_2) + \\
& \beta_{mb_3}(\gamma) MB_{it}\mathbf{I}(K_{R/F,it} > \gamma_2) + \\
& \beta_{cc_1}(\gamma) CC_{it}\mathbf{I}(K_{R/F,it} \leq \gamma_1) + \beta_{cc_2}(\gamma) CC_{it}\mathbf{I}(\gamma_1 < K_{R/F,it} \leq \gamma_2) + \\
& \beta_{cc_3}(\gamma) CC_{it}\mathbf{I}(K_{R/F,it} > \gamma_2) + \\
& \beta_K K_{R/F,it} + \mathbf{BX} + \mu_i + \lambda_t + e_{it}.
\end{aligned} \tag{5}
$$

In such cases, one possibility is to search simultaneously for (γ_1, γ_2) by minimizing $S_2(\gamma_1, \gamma_2)$. While this seems to be a reasonable path to take, the scope of search over the entire grid may be computationally cumbersome.[7] Rather, Hansen (1999) suggests proceeding sequentially by taking threshold $\hat{\gamma_1}$ as given and searching for γ_2 over the threshold variable $K_{R/F}$ by minimizing $S_2(\hat{\gamma_1}, \gamma_2)$.[8] Fixing γ_1 to $\hat{\gamma_1}$, the minimization program to identify the second threshold can be written as:

$$\hat{\gamma_2} = \underset{\gamma_2}{\operatorname{argmin}} \; S_2\Big(\gamma_2\big|_{\gamma_1=\hat{\gamma_1}}\Big). \tag{6}$$

The inference of γ_2 and the determination of its 95% confidence interval are determined as detailed in Appendix A based on bootstrapped samples to test $H_0 : \beta_1(\gamma) = \beta_2(\gamma)$ and $H_0 : \gamma = \gamma_0$. If $\hat{\gamma_2}$ proves significant, Bai (1997) shows that the estimation of $\hat{\gamma_1}$ must be refined by a third stage estimation, taking $\hat{\gamma_2}$ as given, and the refinement minimization program becomes:

$$\hat{\gamma_1} = \underset{\gamma_1}{\operatorname{argmin}} \; S_1\Big(\gamma_1\big|_{\gamma_2=\hat{\gamma_2}}\Big). \tag{7}$$

The algorithm described above can be generalized to any higher order of thresholds. In this paper, we fix the maximum number of possible thresholds to three, implying potentially four types of policy regimes. The advantage of this measure is that it avoids arbitrarily setting the number of regimes. Instead, this number is determined endogenously, giving rise to significant structural breaks that are not time-dependent but dependent upon the threshold variable $K_{R/F}$ representing competencies in renewable energy innovation.[9]

3.2 Endogeneity

A key requirement for a causal interpretation of the coefficients of interest (β_{mb} and β_{cc}) is the exogeneity of the environmental policies variables. This requirement is likely to be

[7] A search grid over (γ_1, γ_2) requires $(N^{.95}_{.05})^2$ regressions. The search grid for a higher order number of thresholds rapidly becomes prohibitive.

[8] Because it is important to have a minimum number of observations in each regime, we restrict the search over $K_{R/F}$ so that the distance between $\hat{\gamma_1}$ and $\hat{\gamma_2}$ amounts to at least a decile.

[9] In the remainder of the paper, we will indifferently call variable $K_{R/F}$ competencies in, knowledge stock of, or technological expertise in renewable energy.

violated in our context for four reasons. First, policy choices depend upon the expected effectiveness of the policy in terms of both economic and environmental outcomes. For instance, a policy maker of a technologically laggard (resp. leading) country can correctly forecast that a given environmental policy will have little (resp. large) effect on the country's capacity to produce renewable energy innovations. As a result, the policy response will positively depend on both the current and the future innovative capacity of the country, leading to an upward bias in the coefficients of interest.

Second, a well-known argument postulates that policy interventions should be temporary and support renewable energy only during an initial phase of technological development when these technologies are significantly more costly than fossil fuel-based technologies. In more mature stages, technological development in renewable energy can proceed independently from the existence of a policy support (Acemoglu et al. 2012), which would give rise to a downward bias in the coefficients of interest. Indeed, there is some evidence in our data that the stringency of MB policies has decreased for certain periods in leading countries such as Germany, Denmark and Spain. These two sources of reverse causality go in opposite directions and may counterbalance each other. Hence, assessing the direction (if any) of the overall reverse causality bias in the estimates of the policy effects remains an empirical issue.

Third, another source of endogeneity arises from errors in the measurement of MB and CC policies. As discussed in detail in Section 3.3, our policy stringency measures assign a time-varying categorical score to each country. This score is in turn based on underlying continuous data on the stringency of several policy instruments, such as taxes and feed-in tariffs. This approach mechanically creates a source of measurement error. Typically, if the measurement error is only on the explanatory variable and normally distributed, it is expected to give rise to a downward bias in the estimates.

Finally, it is worth noting that due to data constraints, we cannot observe the presence and size of subsidies to fossil fuel production, which implies the existence of an omitted variable bias. If, as plausible, fossil fuel subsidies are negatively correlated with both renewable energy policies and with our main dependent variable (i.e., the ratio between renewable and fossil fuel patents), the estimated coefficients of environmental policies should be biased downward.

To address the above concerns on the endogeneity of the MB and CC variables, we use an instrumental variable approach, as discussed in Section 5.1. An important caveat is that our IV strategy should be seen more as a robustness exercise used to corroborate the identification of the thresholds levels of $K_{R/F}$ rather than a way to retrieve the exact effect of MB and CC policies on those thresholds. A precise identification of the effect of each of the policy instruments in each of the different regimes would require a validation using separate regressions for observations belonging to each regime. This is unfeasible given the relatively small number of country-year observations used to estimate our effects of interest. While this is beyond the scope of this paper, such an endeavor should be the focus of future research once data availability constraints are relaxed.

3.3 Data

Our analysis is based on a sample of 34 countries over the years 1990-2012.[10] Below, we discuss in turn the use of patent statistics in our context, the definition of our dependent variable, our proxies for technological competencies and for environmental policies, and the control variables included in our estimation. Descriptive statistics for the sample and for each of the 34 countries are presented in Tables 1 and 2.

3.3.1 Patent Statistics

We use patent data as a proxy for innovation, i.e. the dependent variable, and for accumulated competencies, i.e. the threshold variable. The pros and cons of this proxy with respect to other available innovation proxies, and particularly R&D investments, have been widely discussed (Griliches 1990, Popp et al. 2010). We argue that patent statistics are well suited to capture the level of technological activity of a country in our context for two reasons. First, as discussed above, patents are the result of several polices and institutional settings that span well-beyond mere R&D investments. Second, unlike R&D investments, patent databases are much more detailed than most other sources of information on renewable and fossil investments. Indeed, patent statistics are readily available and exhaustive, and cover a great variety of public and private institutions, essentially business firms, universities, other education and training institutions, and government. Third, patent data allow quantifying each country in terms of innovation performance (the dependent variable) and accumulated competencies (the threshold variable) in renewable energy relative to fossil fuel technologies. Overall, in the absence of systematic information on the private and public funding and on the technological content of R&D investments, the measurement error embodied in patent data is likely to be substantially lower than in R&D data.

Our patent data come from the OECD Green Growth Indicators Database, which includes patent counts for several energy technologies (Haščič et al. 2015, Haščič & Migotto 2015). Renewable energy generation patents include solar, wind, geothermal, marine, and hydro as well as technologies for energy generation from biomass and waste. Fossil-based generation technologies include technologies for improved output efficiency (such as combined heat and power and combined cycles) and technologies for improved input efficiency (such as efficient combustion or heat usage).[11]

3.3.2 Innovation

The share of renewable over fossil fuel patents with a family of two or larger measures the innovation relative performance of countries in these technologies. The first and second rows of Figure 1 show the evolution of renewable energy and fossil-based patents,

[10]The countries included in the analysis are listed in 2.

[11]For a more detailed discussion of the different technologies, please refer to Lanzi et al. (2011), Haščič & Migotto (2015) and the OECD ENV-TECH classification, available at http://www.oecd.org/environment/indicators-modelling-outlooks/green-patents.htm.

respectively, for selected OECD countries, for the BRIICS countries[12] and for the overall sample average. Four facts emerge. First, innovation in renewable energy technologies has been larger than in fossil-based technologies over the sample period. This should be expected because the fossil technologies included in the OECD Green Growth Indicators Database are only those relative to improving the efficiency of fossil fuel energy production, rather than the overall number of fossil technologies. Moreover, fossil innovations are quantitatively fewer than renewables innovations due to the fact that fossil technologies are more mature, while renewables are more likely to be protected by intellectual property rights because they are novel and less incremental. Second, there is a global upward trend in patenting in both renewable and fossil fuel technologies, but the latter grew at a significantly slower pace than the former. Third, OECD countries produce far more patents that BRIICS countries during the period of investigation. But among the BRIICS countries, China seems to take a significant leap forward and invest massively in renewable energy technologies. Fourth, and related to this, while all countries in the sample show a re-direction of innovation in favor of renewable technologies, the phenomenon is more pronounced, but also more heterogenous, in the BRIICS countries than in the largest OECD economies. Among the BRIICS, the dynamics of patenting in China and India clearly stand out.

[Figure 1 about here.]

3.3.3 Threshold Variable and Environmental Policy

Patent data are used to compute the threshold variable, which measures each country's level of technical competencies in renewables relative to fossil-fuels. Specifically, we compute the knowledge stocks for both renewable and fossil energy technologies for each country and each year. The threshold variable $K_{R/F}$ is then defined as the ratio between the former and the latter. We rely on the perpetual inventory method to compute knowledge stocks in renewables and fossil fuel technologies as follows. Details are presented in the Appendix B. The first row of Figure 2 shows the evolution of our threshold variable over time. We observe that $K_{R/F}$ increased significantly in the BRIICS over the sample period, while in large OECD countries, this variable displays more of a U-shape with a turning point concomitant with the Kyoto agreement.

[Figure 2 about here.]

To proxy for environmental policy, which is our other main variable of interest, we extract data from the OECD Environmental Policy Stringency (EPS) Indicator (Botta & Kozluk 2014), which allows to distinguish between market-based MB policies and command-and-control CC regulations (see Appendix B for details on the computation of the indexes). The evolution of these variables is presented in the second and third rows of Figure 2. Note that command-and-control policies are vastly adopted in developed

[12] These countries are Brazil, Russia, India, Indonesia, China and South Africa

countries, while the score is lower and displays less variation in the BRIICS. Market-based policies have a much lower score overall, but their use/stringency increases steadily throughout the sample period, reflecting a gradual replacement of CC policies with MB policies in several countries.

3.3.4 Control variables

To estimate the impact of technological competencies and policy instruments on innovation *ceteris paribus*, we include in the estimation a vector $\mathbf{X}$ of control variables[13], which are quite standard in the literature and discussed in the Appendix B. Two controls deserve to be discussed. First, the pre-sample mean of the dependent variable is computed over the years 1980 and 1989 and is used to control for heterogeneity across countries, as explained in Section 3.1. Second, the (log of the) overall stock of knowledge is built using information on all patents applied for by inventors of each country each country i at time t following the formula used for the renewable and fossil patent stocks presented in Appendix B. This variable conditions the estimates on overall trends in patenting activities, which are country-specific and time-varying. Indeed, countries with a larger total patent stock (e.g. USA, Japan, Germany) may be less specialized in a particular energy technology than countries with a small stocks because they are more likely to be actively engaged in both types of technologies. Tables 1 and 2 present descriptive statistics of all the variables included in subsequent econometric analyses.

[Table 1 about here.]

[Table 2 about here.]

4 Econometric Results

4.1 Baseline Results

Table 3 shows a first set of results. Model 1 is a parsimonious specification that includes only time fixed effects, the log-transformed ratio of renewable and fossil knowledge stocks $K_{R/F}$ (the threshold variable) and the pre-sample mean of the dependent variable. In line with related papers of Aghion et al. (2016) and Noailly & Smeets (2015), the coefficients of both $K_{R/F}$ and the pre-sample mean are positive and statistically significant at 1% level. This confirms our hypothesis of persistence in direction of innovation in energy technologies: countries with experience in renewables – relative to fossil fuel – have a comparative advantage in producing further renewable energy innovation – relative to fossil fuel innovation. It also reinforces the idea that in the realm of energy innovation, there is a first-mover advantage for early innovators in a particular field, i.e. brown vs.

[13]These variables are: the presample mean of the dependent variable, the total stock of knowledge in a given country, GDP per capita, average years of schooling, the share of electricity and heat exports over total electricity production and Coal Dependence

green. This, however, also implies that laggard countries can be locked in a fossil fuel technological paradigm.

Model 2 includes environmental policies, namely MB and CC. Both variables take positive values. However, the coefficient associated with MB policies fails to reach acceptable levels of significance (p-value=0.147). This surprising result is however not robust. In Model 3, which includes additional control variables, the coefficient associated with the MB variable is similar in magnitude to that estimated in Model 2, but is now statistically significant. Conversely, the coefficient associated with CC, which becomes smaller in size, is now imprecisely estimated (p-value=0.145). On the whole, our results corroborate the well-accepted fact that environmental policies have a positive effect in redirecting innovation from brown to green technologies (Aghion et al. 2016). However, the lack of precision in the point estimates may conceal heterogeneity in the effects of MB and CC policies on innovation.

Two of the control variables included in Model 3 emerge as particularly strong. Electricity exports and the total stock of knowledge positively influence our dependent variable, implying that they are associated with a redirection of innovation from fossil to renewable technologies. Concerning the latter variable, this suggests that countries located at the overall technological frontier tend to innovate more in renewables. Indeed, innovation in renewables is still a highly exploratory path to take, and technologically advanced countries are better equipped to follow this course. Electricity exports behave as expected. Exports act as a buffer to handle the intermittency of renewable electricity generation, making innovation in renewable relatively more attractive. Finally, the inclusion of the control variables yields non-significance of the pre-sample mean. This should be expected, since the pre-sample mean catches the countries' unobserved heterogeneity, which is essentially captured in variables such as GDP per capita, human capital, exports and total knowledge stock. This implies that the series of control are successful in grasping the specific – regulatory and institutional – features of countries in our sample.

[Table 3 about here.]

The discussion in Section 2 suggests that environmental policies play a role in redirecting energy innovation. Models 2 and 3 provide preliminary evidence in this respect, but do so by averaging away the heterogeneity in the policy effectiveness for countries with different level of relative competencies. Model 4 tackles this issue by interacting $K_{R/F}$ with the two policy variables. Two interesting results deserve to be discussed. First of all, the Log-Likelihood Ratio (LR) test confirms that Model 4 brings significant explanatory power when compared with Model 3 (LR-test of 54.05 with a p-value of zero). In other words, the specification with the interaction terms outperforms the specification without them in explaining the direction of innovation in energy technologies. Second, the coefficients of the interaction terms indicate that both CC and MB are more effective in redirecting innovation towards renewable energy technologies when the relative stock of competencies in these technologies is larger.

These results conform to our claim that the indirect effect of environmental policies on the direction of energy innovation is proportional to the degree of specialization in renewable as opposed to fossil-fuel technologies. One possible explanation is that countries with more competencies in fossil-fuel than in renewable technologies will try to meet the environmental requirements of such policies by making fossil fuel energy more efficient. These results implicitly suggests that direct innovation policies may be required to elicit the indirect innovation effect of MB and CC policies. As argued in previous studies (Popp 2006, 2016, Mazzucato 2015), targeted public R&D plans represent a good example of chief policy to boost knowledge accumulation in specific technological fields.

4.2 Threshold Specification Results

The interaction model confirms that the effect of environmental policies is contextual, but assumes away the possibility of discontinuities in policy effectiveness. Specifically, the model does not allow for a discontinuous switch in the selection of appropriate policies, but only a difference in the two policy effects associated with the relative level of competencies. As mentioned in Section 3.1, we use Hansen's threshold model to determine whether such discontinuities exist and, if so, what are the values of the threshold(s) that delimit different policy regimes as dependent on $K_{R/F}$. For the sake of exposition, we first discuss the number and levels of the thresholds which emerge from the model, and then present the results of the estimation of the threshold model, although both steps are simultaneous.

4.2.1 Determination of the thresholds

Table 4 presents the estimated thresholds and their associated F-statistics: F_1, where the null hypothesis H_0 posits the absence of threshold and the alternative hypothesis H_1 states that there is at least one threshold; F_2 as a test of the existence of one threshold (H_0) against the alternative hypothesis of at least two thresholds (H_1); F_3 as a test of the existence of two threshold (H_0) against the alternative hypothesis of at least three thresholds (H_1). The main message of Table 4 is that policy effectiveness exhibits threshold effects: both the F_1 and the F_2 tests for the single threshold and double threshold models are highly significant, with bootstrapped p-values of 0.000, and 0.094, respectively. Conversely, the F_3 test for the three-threshold model is not significant, with a bootstrap p-value of 0.736. Overall, the Hansen's procedure provides strong evidence that there are two thresholds, and hence three regimes, linking MB and CC policies with directed energy innovation.

Table 4 also displays the point estimates of the two thresholds, 2.856 and 1.706, which correspond to respectively the 88^{th} and 47^{th} percentiles of the distribution of the $K_{R/F}$ threshold variable. The confidence intervals around the estimated thresholds are small, indicating little uncertainty about the location of the level of $K_{R/F}$ needed to switch from one regime to another. The plots of the concentrated likelihood ratio function, which are shown in Figure 3, provide further information about the threshold estimates. In particular, the graph for the one-threshold model indicates a first threshold, which is where the LR hits zero at the 88^{th} percentile of the threshold variable, and a second major fall in the LR at the 47^{th} percentile. The Hansen's procedure uses the values of the estimated thresholds to create dummy variables for the different regimes, which we are then interacted with the policy variable(s). This means including three variables for each of the policy instruments (CC and MB), indicating whether a given observation belongs to the first, second or third regime, as detailed below.

[Table 4 about here.]

[Figure 3 about here.]

A legitimate question is whether the threshold specification outperforms the interaction specification of Model 4. The answer lies in the last two rows of Model 5 displayed in Table 5. We use the LR-test to compare the two-threshold model with 15 explanatory variables with the interaction model which has 11 explanatory variables. Note that the difference between the two models is not the use of more information coming from an additional explanatory variable; rather, the difference lies in the way we exploit how the level of expertise $K_{R/F}$ interacts with the two policy variables. In the LR-test, the null hypothesis H_0 is that any change in the level of expertise in renewable energy relative to fossil fuel energy modifies policy effectiveness linearly (i.e. the interaction model is corroborated), whereas the alternative H_1 is that there are several regimes between which policy effectiveness differs significantly and within which policy effectiveness is stable (i.e. the threshold model is corroborated). The key result here is that with a critical probability value of 0.060, we can reject the null hypothesis H_0 and accept the alternative hypothesis H_1: there are regimes between which policy effectiveness differs significantly and within which policy effectiveness is stable.

4.2.2 Estimation Results

The results of the estimation of the two-threshold model are presented in Table 5, which strongly supports our conjecture that the selection of the appropriate policy instrument switches discontinously across the different regimes, which are defined by the country's degree of specialization in renewable technologies as compared to fossil-based technologies.

In the first regime where $K_{R/F}$ is low, only the threshold variable is positive and significant, while the CC and MB policy indexes are not statistically significant. This implies that in the first regime, policy effectiveness of either CC or MB is simply nil, which includes almost half of our country-year observations (47%). Importantly, these results contradict the paradoxical results stemming from the interaction model which suggest a counter-productive effect of environmental policies on the direction of technical change when the level of expertise is particularly low. The second regime, which is characterized by values of $K_{R/F}$ between the median and the 87^{th} percentile, gives similar results, with the important difference that the coefficient associated with CC policies is positive and almost significant (p-value of 0.146). While this coefficient is not precisely estimated, this result suggests that CC policies may be somewhat more effective than MB policies in redirecting energy innovation towards renewables for countries that lack specialization in any of the two technological domains. Lastly, in the third regime, the positive effect of the threshold variable is compounded by a positive and statistically significant effect of the MB index. Therefore, a country that has accumulated a considerable amount of experience in renewables vis-a-vis fossil technologies (the top 12% of the country-year observations in our sample) can avoid the use of command-and-control policies and rely exclusively on market-based policies.

Figure 4 provides a graphical representation of the size of the policy effects in different regimes. In particular, we quantify the effect of a one standard deviation of each policy index around the mean in each regimes. Market-based policies have a large impact on the direction of technical change in the third regime, with a one-standard deviation increasing the ratio of renewable to fossil patent by 0.55, which represents 40% of the average value of the dependent variable $P_{R/F}$. Notice that the insignificant effect of MB policies in the second regime is less than a fifth of that in the third regime. CC policies appear more useful in redirecting energy innovation in the crucial second regime, although their effect is only barely significant. The estimated impact is moderately large with one-standard deviation increase in CC policies accounting for an 8% increase in the expected number of renewable patents relative to fossil fuels.

Given the nature of our dependent variable, which is defined as the ratio of renewable over fossil fuel innovation, a legitimate question raised by these results is the exact mechanism through which MB and CC policies affect the direction of energy innovation. A key issue to understand the mechanisms is whether (and how) MB and CC affect the numerator and/or the denominator of our ratio. Table 5 displays two additional models, which explore separately the effect of the policy instruments with respect to the level of renewable (Model 6) and fossil fuel innovation (Model 7). As in Model 5, the MB and CC variables are interacted with dummy variables representing each of the three regimes, where the previously estimated threshold values are taken as given. This accounts for the fact that the level of innovation in green or brown technologies still depends on the relative degree of technological specialization, which captures the opportunity cost of not investing in the alternative technology. The two models provide important insights on the mechanisms at work. Specifically, they indicate that MB policies in the second and third regimes positively impact renewable energy innovation. Conversely, CC policies impact the direction of innovation by depressing fossil-based innovation in the second regime (see also Figure 4).

The focus on the effectiveness of the two policy instruments on the level of clean vs. brown innovation points to the second regime as the crucial period where an appropriate policy mix must be implemented. This policy mix is characterized by a positive impact of MB policies on renewable innovation and a negative impact of CC policies on fossil-based innovation. Clearly, command-and-control policies, by setting up emissions quotas, send a clear orientation to private actors on the future of fossil fuel within a country and deter brown innovation. However, CC policies do not spur innovation in renewables, and only the support of MB policies comes into play and provides actors with the necessary incentives to actually undertake invention activities in new carbon-free energy solutions.[14]

In sum, command-and-control policies act as a *stick* to properly orientate actors in a regime characterized by a not yet well-defined specialization in energy technologies (first threshold is at 47%), but must be combined with the MB policies, which act as a *carrot* in providing direct monetary incentives to the green innovators. Beyond a certain level of comparative advantage in renewables (88%), only the carrot is effective in reinforcing green technological specialization.

[Table 5 about here.]

[Figure 4 about here.]

5 Discussion

5.1 Robustness Checks

In this section, we show that our results are robust to a series of alternative specifications, which are presented in Table 6 alongside our favourite specification (Model 5) for the sake of comparison. Before commenting each robustness exercize, we note the high persistence of the estimated threshold percentiles throughout Models 5 to 10. In all cases, our model estimates two thresholds, located near the median and near the 9^{th} decile.

First and foremost, to reinforce a causal interpretation of the policy effects, we begin by estimating our favourite specification using an IV strategy. As Subsection 3.2, our least square estimates could be biased due to three different reasons: reverse causality, omitted variable bias and measurement errors. The direction of bias in the case of reverse causality cannot be determined *a priori*, while in the case of both omitted variable and measurement errors, one would expect a downward bias. To perform an IV estimation, we select two external instruments, which are arguably correlated with our policy stringency scores but not with the direction of technical change. Our first instrument is a shift-share variable constructed as an interaction between population growth and the pre-sample mean of PM2.5 concentration, i.e. the concentration of particles with an aerodynamic diameter of less that 2.5 μm.[15] The instrument $PM2.5_{i,t}$ is built as follows: $PM2.5_{i,t} = (1 + g_{POP_{i,t}})PM2.5_{i,t-1}$, where $PM2.5_{i,t=0} = PM2.5_{i,1990}$ represents emission concentrations in 1990, and g_{POP_t} is the growth of the population in country i at time t. This instrument captures the counterfactual level of PM2.5 concentration that

[14] Note that the impact of MB policies in the second regime is very heterogeneous, and the combined effect on the direction of technical change is not precisely estimated.

[15] The source of this data is Brauer et al. (2016), as reported by WDI (2016). Satellite measurements of concentrations (ug/m3) measure the concentration levels in a given country in a given year. These in turn are determined by a wealth of anthropogenic and non-anthropogenic factors, namely: anthropogenic emissions, background concentrations, natural emissions (dust, vegetation, natural aerosols, etc..), secondary pollution (particulates formed in the atmosphere), transboundary pollution (i.e., pollution originating in other countries).

would be uniquely attributed to population dynamics. The exclusion restriction here is that, conditional on a set of controls for the country's size and wealth (such as total stock of patents and GDP per capita), this counterfactual level of emissions does not alter the relative incentives of pursuing renewable energy rather than fossil fuel innovation. We are confident that this restriction is satisfied because fossil-fuel plants have a limited impact on PM2.5 emissions, and hence concentrations, which are primarily caused by the transport sector. Therefore, the effort of the fossil-fuel lobbies against this regulation should be limited. Further, the concentration of PM2.5 emission is also affected by geographical and atmospheric factors that are partially unrelated with effective PM2.5 emissions. This does not affect the strength of the instrument that is corroborated by the first-stage results, which are presented in Appendix C.[16] That the instrument is strong and positively correlated with both CC and MB policies is expected as policy makers adopt environmental policies to respond to emissions above the norm, especially for diffused sources like PM2.5 to which citizens are more sensitive.

The second instrument we use is the length of time for which a country has had consolidated and durable democratic institutions.[17] This instrument simply captures the fact that democratic countries tend to approve stricter environmental policies and has been used by the closely related paper of Nesta et al. (2014), to which we refer for a more detailed discussion. The first-stage results in Appendix C show that this second instrument is strong and correlated with both CC and MB policies. However, while the estimated coefficient is positive in the CC fist stage regression, it is negative in the MB specification. Note however that this last result can be totally attributed to the inclusion of the control variables, as a reduced model with regresses MB only on TENSYS and time dummies shows a positive and significant effect of the latter[18]. Overall, the F-test of excluded instruments corroborates our choice regarding both instruments.

The second stage results, presented in Model 8, are consistent with those presented so far, and indicate a downward bias in the least square estimates.Not only is the coefficient associated with MB policies in the third regime more than double that presented in the preferred model, but the coefficient associated with CC policies in the second regime also becomes significant and considerably larger.

We are cautious in giving full credit to these estimates as capturing the true magnitudes of the policy effects in different regimes because our exclusion restrictions are neither theory-driven nor extensively validated in previous literature, with the exception of the paper of Nesta et al. (2014). However, the policy variation captured by our instruments is arguably more exogenous than that of the original policy indexes. We are thus confident that, at least, this robustness exercise corroborates our main findings regarding the location of the regime switches and the qualitative importance of CC and MB policies in different regimes.

[16] Appendix C presents the results of the first stage estimation where MB and CC are instrumented with the series of exogenous variables $\mathbf{X}$ in equation 3 and the two additional instruments. Note that the first column of Table A1 presents the second stage of the IV procedure estimating equation 1.

[17] The data on TENSYS are sourced from the Database on Political Institutions (Thorsten et al. 2001, Cruz et al. 2016).

[18] Results are available upon request.

Second, Model 9 presents the results of the estimation when restricting attention to patents of higher economic value. This is obtained by considering only innovations that are protected in at least four, not two, countries. The results differ slightly from those of the base model 5 because the estimated thresholds are higher, indicating that switching from the first to the second regime and from the second to the third regime occur at higher levels of the threshold variable. The estimated thresholds are indeed associated with the $94th$ and the $65th$ percentiles. This is in line with the expectation that innovation of higher quality is more difficult to achieve.[19] Another important finding of Model 9 is that command-and-control policies do not seem to matter for directing technical change at the frontier. These remarks are consistent with the third regime of Model 5 where only market-based policy instruments matter.

Third, Models 10 shows the results using a broader definition of our dependent variable, and specifically including in the computation of the numerator of the threshold variable also patents relative to "supporting" technologies that ease the diffusion of renewable energy sources in the electricity system. These are energy storage and smart grids. The former contributes to smoothing the variable of reneweable energy supply, which is one of the main difficulties linked with integration high shares of renewables in the energy system (Verdolini et al. 2016, Carrara & Marangoni in press), while the latter allows distributed generation as opposed to centralized generation of energy. We observe that the results are robust.

Whether MB and CC promote the diffusion of renewable technologies, rather than mere innovation, is a key issue because laggard countries can use MB and CC policies first to favour the diffusion of renewable energy technology and then, through learning effects, to become green innovators. Taking the estimates regimes as given, Model 11 extends the focus of our analysis from the dynamic incentives of policy instruments to their impact on technology diffusion. In details, the dependent variable is now calculated as the percentage of electricity generation coming from renewable sources over total electricity produced in a given country i in a given year t.[20] As in Models (6) and (7) in Table 5, we take the estimates thresholds as given. To control for the overall dynamics of energy generation in a given country, we substitute the Total Stock of Knowledge variable with a variable measuring Total Primary Energy Supply in the country (from the IEA). Model 5 in Table 5 shows that policy effectiveness in different regimes is qualitatively similar for diffusion and innovation. Specifically, CC policies are associated with higher shares of renewable energy generation in the second regime, while MB policies are most effectively in promoting renewable penetration in the third regimes. We can hence conclude that a demand-pull strategy based on diffusion first and then innovation does not allow laggard countries to lock out from brown technologies.[21]

[19]The fact that the required level of technological specialization increases with patent quality also seems intuitive. Although the order of detection of the threshold may swap from one specification to the other, this altogether is a source of confidence in the results stemming from Hansen's threshold specification.

[20]The results are similar if one includes also statistics relative to heat generation, and they are available upon request.

[21]As a final comment, note that our contribution is specifically designed to detect discontinuities in

[Table 6 about here.]

5.2 Country Diagnostics

Our results allow establishing a set of diagnostics to measure the adequacy of each country's policy mix with its level of expertise in renewable relative to fossil energy technologies, which help highlighting successes and failures. This is especially important to draft policy recommendation for countries which lack technological specialization in either fossil or renewable energy technologies, but need to implement environmental policies to comply with international agreement. Specifically, our results can be used to identify the policy mix which is most effective in promoting dynamic incentives to redirect innovation towards more sustainable, green technologies. To this end, Table 7 displays the position of a country in a percentile within the threshold variable $K_{R/F}$ and market-based and command-and-control policy indexes for the entire period 1990-2012. It also displays each of these variables for three subperiods, where the first period gathers the pre-Kyoto years (1990-1997), the second period concerns the post-Kyoto pre-great recession years (1998-2007) and the last period ranges from 2008 to 2012. Looking at the mean of the threshold variable by subperiod, the redirection of innovation towards renewables in the third period is striking, with the average country located in the 72^{th} percentile of $K_{R/F}$ compared with the 42^{th} and the 45^{th} in the first and second period, respectively.[22]

Table 7 highlights a fundamental difference between countries which adopt environmental policies resulting in a clear technological direction and countries that do not. We discuss these differences illustrating a successful case, two failure cases, and then concentrate on Eastern European countries and the BRIICS countries more specifically.

The typical successful example comes from Denmark. In the pre-Kyoto period, Denmark had not yet reached the required level of expertise in renewable energy relative to fossil fuel energy (41^{st} percentile, below the 47^{th}). With the new millennium, Denmark chooses to increase both MB and CC policies (reaching .45 and .42, respectively). This is in tune with our findings that both types of policies are useful in providing private

the dynamic incentives of domestic policies. These are by far the most important policy driver identified in the literature. Recent empirical evidence points to a considerably smaller, yet significant, effect of foreign policies in promoting domestic innovation (Peters et al. 2012, Dechezleprêtre & Glachant 2014). In our model, the role played by foreign policies is accounted for in a general way with the inclusion of time fixed effects. A more thorough investigation would require, on the one hand, the computation of a country-specific, time varying index of exposure to foreign policies and, on the other hand, a significant complication of the empirical set up of the threshold model. In unreported analyses available upon request, we built simple proxies of foreign policies, as the average values of MB and CC policies in all countries $i \neq j$, and introduced them in the vector of control variables. The results are very similar to the ones presented above, thereby corroborating our findings.

[22] Unreported analyses of variance (ANOVA) show that both cross-country and time variations explain a substantial share of the variance in the sample. For the threshold variable $K_{R/F}$, ANOVA results show that cross-country variations explain 50% of the variance and that time variations explain 21%. For MB (resp. CC policies), the same decomposition shows that cross-country variations explain 28% (resp. 27%) and that time variations explain 43% (resp. 45%). It is thus important to consider the dynamics of countries individually.

investors with a clear orientation of the technological direction where the country wants to embark. Yet, in the post-crisis era, Denmark has reached a level of expertise that allows the country to switch to the third regime $K_{R/F,DEN} = 96.6$. Meanwhile, Denmark is the only country where MB policies moderately outperform CC policies in the last period, and increasingly so in the most recent – unreported – years.

Now focusing on failures, two examples are France and Sweden. At a first glance, France does not seem to fit in our story. The lack of an adequate MB support in the nineties has led to the full dissipation of the French early advantage in renewable technologies. With accumulated competencies in the 94^{th} percentile of $K_{R/F}$ in the first period, France is the only country that is in the third regime in the first period. France was then in an ideal position to implement ambitious MB policies before other countries and keep its relative technological advantage. Instead, its choice to fully specialize in the nuclear energy has led to a reduction of resources devoted to the development of renewable energy sources. In the same vein, Sweden represents a case of failure predicted by our model. A revealed specialization in fossil fuel technologies (on average 27^{th} percentile) undermined the dynamic effect of ambitious environmental policies. Correctly predicting this structural disadvantage, Swedish policy-makers did not actively invest in wind and solar R&D compared with other OECD countries (see, e.g., Figures 2-3 in Popp 2015).

Transition economies joined the EU (Poland, Hungary, the Slovak Republic, the Czech Republic and Slovenia) with a clear agenda to gradually comply with EU environmental regulations upon their entry in 2004. This represented a big policy push that is also evident in our data. For all these countries, both the MB and the CC indexes move from nearly zero initially to values in line with the sample mean in the second period. Looking at the last two subperiods characterized by this policy push, countries in the position to adopt ambitious policies (Czech Republic, Hungary and the Slovak Republic) succeeded in redirecting innovation towards renewable energy technologies. Of these three countries, Slovenia has been more reluctant to adopt ambitious CC policies compared to Hungary and the Czech Republic. In line with our findings, this policy gap has been translated into a less pronounced redirection of innovation in Slovenia compared with the other two countries.

The final case is that of the BRIICS countries. These also started regulating emissions from fossil fuel generation only recently, but, absent from the policy push of the EU membership, at a significantly lower level of stringency than transition economies. China already started a virtuous circle reaching the 97^{th} percentile of knowledge accumulation and specialization $K_{R/F}$ in the last period, sharply contrasting with the 49^{th} percentile of the second period, making it possible for China to implement the third type of policy mix. The reasons underlying the Chinese green turnaround are not fully clear. Green policies remain rather timid, and lower wages may have attracted foreign investors to develop given segments of the renewable sector. Other BRIICS countries still suffer from a general lack of total knowledge, including energy-related technological expertise.[23] As

[23] The country diagnostic Table highlights the importance of controlling for the total patent stock in our regressions. Indeed, countries with a large total patent stock (e.g. USA, Japan, Germany) are less

highlighted by the examples of India and Indonesia, which are at the bottom percentiles of $K_{R/F}$, policies *directly* targeting innovation, i.e. to develop the country's absorptive capacity, are of paramount importance in these cases.

[Table 7 about here.]

6 Conclusions

This paper has analyzed the effectiveness of different environmental policies instruments in terms of dynamic incentives to redirect technical change towards clean technologies. The question is admittedly not new, but our approach to providing an answer is innovative for at least two reasons. First, we use threshold econometric models (Hansen 1999) to test whether policy effectiveness displays discontinuities depending on the relative specialization of a country in renewables vis-á-vis fossil fuel technologies. This choice is corroborated by the fact that the threshold model explains the largest share of the variance in innovation compared to alternative specifications. Second, in the context of thresholds models, we compare the effectiveness of the dynamic incentives of two types of environmental policies, market-based and command-and-control policies.

Our results can be summarized as follows. We provide evidence on the existence of three regimes, with thresholds located at the 47^{th} and the 88^{th} percentiles of relative technological specialization. In the first regime, neither MB nor CC policies are effective in promoting a switch towards renewable energy innovation. In the second critical regime, command-and-control policies act as a *stick* by depressing brown innovation and properly orientating actors in countries without a yet well-defined specialization in clean technologies. In these countries, market-based policies compound this effect by acting as a *carrot* which provides incentives to the green innovators. However, beyond a certain level of comparative advantage in renewables, a third regime emerges where only the carrot is effective in reinforcing green technological specialization. Finally, our results are robust to several robustness checks and alternative specifications, which include an IV approach and different definitions of (renewable) energy innovation.

These results imply that implementing policies in support of innovation in renewable energy is highly contextual. When knowledge accumulation and specialization is low, countries need to strengthen their level of green relative to brown technological competencies before they can fully benefit from the dynamic incentives of environmental policies. Therefore, our conclusion is that policies aiming at the accumulation of scientific and technical expertise appear to be a critical. We mainly think of basic R&D investments and education to build and expand national capabilities. By developing their absorptive capacity, laggard countries will be able to satisfactorily identify, assimilate and eventually exploit green competencies invented elsewhere. Moreover, without such capabilities, a laggard country will simply not be able to fully exploit the dynamic incentives of environmental policy instruments and will not catch up with frontier countries. Finally, we illustrate cases where environmental policies have been effective in

specialized than countries with a smaller knowledge stocks.

redirecting energy innovations in laggard countries. The case of transition economies that joined the EU is encouraging in that such external push for environmental policies can become an opportunities to redirect energy innovation also for countries without a clear green specialization. The Paris agreement can represent a similar opportunity for other developing and emerging economies, provided that the right enforcement mechanisms are put in place.

References

Acemoglu, D., Aghion, P., Bursztyn, L. & Hemous, D. (2012), 'The environment and directed technical change', *American Economic Review* **102**(1), 131–66.

Acemoglu, D., Aghion, P. & Zilibotti, F. (2006), 'Distance to frontier, selection, and economic growth', *Journal of the European Economic Association* **4**, 37–74.

Aghion, P., Dechezleprêtre, A., Hémous, D., Martin, R. & Reenen, J. V. (2016), 'Carbon Taxes, Path Dependency, and Directed Technical Change: Evidence from the Auto Industry', *Journal of Political Economy* **124**(1), 1 – 51.

Aghion, P. & Howitt, P. (2006), 'Joseph schumpeter lecture appropriate growth policy: A unifying framework', *Journal of the European Economic Association* **4**(2-3), 269–314.

Arthur, B. (1989), 'Competing technologies, increasing returns, and lock-in by historical events', *Economic Journal* **99**, 116–31.

Bai, J. (1997), 'Estimating Multiple Breaks One at a Time', *Econometric Theory* **13**(03), 315–352.

Blundell, R., Griffith, R. & Windmeijer, F. (2002), 'Individual effects and dynamics in count data models', *Journal of Econometrics* **108**, 113–131.

Botta, E. & Kozluk, T. (2014), 'Measuring Environmental Policy Stringency in OECD Countries: A Composite Index Approach', *OECD Economics Department Working Papers, No.1177* .

Brauer, M., G, F., J, F. & van Donkelaar A et al. (2016), 'Ambient air pollution exposure estimation for the global burden of disease 2013', *Environmental Science and Technology* **50**, 79–88.

Calel, R. & Dechezleprêtre, A. (2016), 'Environmental Policy and Directed Technological Change: Evidence from the European Carbon Market', *The Review of Economics and Statistics* **98**(1), 173–191.

Carrara, S. & Marangoni, G. (in press), 'ncluding system integration of variable renewable energies in a constant elasticity of substitution framework: The case of the witch model', *Energy Economics* (10), 3150–3182.

Cohen, W. M. & Levinthal, D. (1989), 'Innovation and learning: the two faces of r&d', *Economic Journal* **99**(September), 569–596.

Cruz, C., Keefer, P. & Scartascini, C. (2016), 'Database of political institutions: Changes and variable definitions'.

Dechezleprêtre, A. & Glachant, M. (2014), 'Does foreign environmental policy influence domestic innovation? evidence from the wind industry', *Environmental and Resource Economics* **58**(3), 391–413.

Dosi, G. (1982), 'Technological paradigms and technological trajectories: A suggested interpretation of the determinants and directions of technical change', *Research Policy* **11**(03), 147–162.

Feenstra, R. C., Inklaar, R. & Timmer, M. P. (2015), 'The next generation of the penn world table', *American Economic Review* **105**(10), 3150–3182.

Freeman, C. (1982), *The Economics of Industrial Innovation*, Pinter Publisher, London, UK.

Galor, O. & Zeira, J. (1993), 'Income distribution and macroeconomics', *The review of economic studies* **60**(1), 35–52.

Griliches, Z. (1990), 'Patent Statistics as Economic Indicator: A Survey', *Journal of Economic Literature* **28**(4), 1661–1707.

Haščič, I. & Migotto, M. (2015), 'Measuring environmental innovation using patent data', *OECD Science, Technology and Industry Working Papers 2015/89* .

Haščič, I., Silva, J. & Johnstone, N. (2015), 'The Use of Patent Statistics for International Comparisons and Analysis of Narrow Technological Fields', *OECD Science, Technology and Industry Working Papers 2015/05* .

Hansen, B. E. (1999), 'Threshold effects in non-dynamic panels: Estimation, testing, and inference', *Journal of econometrics* **93**(2), 345–368.

Howitt, P. & Mayer-Foulkes, D. (2005), 'R&D, Implementation, and Stagnation: A Schumpeterian Theory of Convergence Clubs', *Journal of Money, Credit and Banking* **37**(1), 147–177.

IEA, I. E. A. (2016), 'World energy statistics'.

Johnstone, N., Haščič, I. & Popp, D. (2010), 'Renewable energy policies and technological innovation: Evidence based on patent counts', *Environmental and Resource Economics* **45**, 133–155.

Kline, D. (2001), 'Positive feedback, lock-in, and environmental policy', *Policy Sciences* **34**(1), 95–107.

Kline, S. & Rosenberg, N. (1986), *The positive sum strategy: harnessing technology for economic growth*, National Academy Press, Washington DC, USA, chapter An Overview of Innovation, pp. 275–305.

Krysiak, F. C. (2008), 'Prices vs. quantities: The effects on technology choice', *Journal of Public Economics* **92**(5-6), 1275–1287.

Lanzi, E., Verdolini, E. & Haščič, I. (2011), 'Efficiency-improving fossil fuel technologies for electricity generation: Data selection and trends', *Energy Policy* **39**(11), 7000–7014.

Mazzucato, M. (2015), *The entrepreneurial state: Debunking public vs. private sector myths*, Anthem Press.

Murphy, K. M., Shleifer, A. & Vishny, R. W. (1989), 'Industrialization and the big push', *Journal of political economy* **97**(5), 1003–1026.

Nesta, L., Vona, F. & Nicolli, F. (2014), 'Environmental policies, competition and innovation in renewable energy', *Journal of Environmental Economics and Management* **67**(3), 396–411.

Nicolli, F. & Vona, F. (2016), 'Heterogeneous policies, heterogeneous technologies: The case of renewable energy', *Energy Economics* **56**(C), 190–204.

Noailly, J. & Smeets, R. (2015), 'Directing technical change from fossil-fuel to renewable energy innovation: An application using firm-level patent data', *Journal of Environmental Economics and Management* **72**(C), 15–37.

Patel, P. & Pavitt, K. (1997), 'The technological competencies of the world's largest firms: complex and path-dependent, but not much variety', *Research Policy* **36**, 141–156.

Peri, G. (2005), 'Determinants of knowledge flows and their effect on innovation', *Review of Economics and Statistics* **87**, 308–322.

Peters, M., Schneider, M., Griesshaber, T. & Hoffmann, V. (2012), 'The impact of technology-push and demand-pull policies on technical change: does the locus of policies matter?', *Research Policy* **41**(8), 1296–1308.

Popp, D. (2002), 'Induced innovation and energy prices', *American Economic Review* **92**(1), 160–180.

Popp, D. (2003), 'Pollution control innovations and the clean air act of 1990', *Journal of Policy Analysis and Management* **22**(4), 641–660.

Popp, D. (2006), 'They don't invent them like they used to: an examination of energy patent citations over time', *Economic of Innovation and New Technology* **15**, 753–76.

Popp, D. (2015), Using scientific publications to evaluate government r&d spending: The case of energy, Technical report, National Bureau of Economic Research.

Popp, D. (2016), 'Economic analysis of scientific publications and implications for energy research and development', *Nature Energy* **1**(16020).

Popp, D., Newell, R. & Jaffe, A. (2010), Energy, the environment, and technological change, *in* B. Hall & N. Rosenberg, eds, 'Handbook of the Economics of Innovation', Elsevier, pp. 873–937.

Requate, T. (2005), 'Dynamic incentives by environmental policy instruments - a survey', *Ecological Economics* **54**, 175–195.

Rodrik, D. (2005), ‘Growth strategies’, *Handbook of economic growth* **1**, 967–1014.

Rosenberg, N. (1982), *Inside the Black Box: Technology and Economics*, Cambridge University Press.

Taylor, M. (2012), ‘Innovation under cap-and-trade programs’, *Proceedings of the National Academy of Science* **109**(13), 4804–4809.

Thorsten, B., Clarke, G., Groff, A. & andPatrick Walsh, P. K. (2001), ‘New tools in comparative political economy: The database of political institutions’, *World Bank Economic Review* **15**(1), 165–176.

Verdolini, E. & Bosetti, V. (2017), ‘Environmental policy and the international diffusion of cleaner energy technologies’, *Environmental and Resource Economics* **66**(3), 497–536.

Verdolini, E. & Galeotti, M. (2011), ‘At home and abroad: An empirical analysis of innovation and diffusion in energy technologies’, *Journal of Environmental Economics and Management* **61**(2), 119–134.

Verdolini, E., Vona, F. & Popp, D. (2016), ‘Bridging the gap: Do fast reacting fossil technologies facilitate renewable energy diffusion’.

Vona, F., Marin, G. & Consoli, D. (2017), Measures, Drivers and Effects of Green Employment: Evidence from US Local Labor Markets, 2006-2014, SPRU Working Paper Series 2017-13, SPRU - Science and Technology Policy Research, University of Sussex.

WDI (2016), ‘World development indicators database’.

Weitzman, M. L. (1974), ‘Prices vs. Quantities’, *Review of Economic Studies* **41**(4), 477–491.

Appendix A. Determination of the 95% confidence interval for the estimated thresholds

Once threshold $\hat{\gamma}$ has been identified, two additional steps are needed. The first one regards the significance of the threshold and tests whether the two identified regimes are significantly different from one another, the null hypothesis being $H_0 : \beta_1 = \beta_2$, where 1 and 2 refer to the first and second regimes, respectively. The second step concerns efficiency in order to determine the 95% confidence interval of the threshold likely values, with the null hypothesis being $H_0 : \hat{\gamma} = \gamma^*$.

Concerning the first step, inference on $\hat{\gamma}$ is achieved by generating bootstrapped samples and comparing model 1 with model 3. First, observe that specification 1 is nested in 3, which is a more general representation of the effect of policies on green innovation. Hence we can rely on the use of a likelihood ratio test to determine whether specification 3 conveys more information than specification 1. Second, given the panel nature of the data, we randomly draw (with replacement) countries in order to produce a bootstrapped sample of size N. Using the bootstrapped sample, we then estimate specifications 1 and 3 and perform the likelihood ratio test. We repeat this procedure a sufficiently large number of times and count the number of times for which the likelihood ratio test fails to reject the null hypothesis that the specification 1 brings as much information as specification 3. By way of example, for the case of MB policies the null hypothesis is $H_0 : \beta_{mb1}(K_{R/F} \leq \gamma) = \beta_{mb2}(K_{R/F} > \gamma)$, which implies the absence of two distinct regimes. The share of samples failing to reject the null hypothesis of no threshold is used as the critical probability value.

The second step is concerned with efficiency, with the null hypothesis being $H_0 : \hat{\gamma} = \gamma^*$. We follow Hansen (1999) and use the likelihood ratio statistics $LR_1(\gamma^*)$ as follows:

$$LR_1(\gamma) = \frac{S_1(\gamma) - S_1(\hat{\gamma})}{\hat{\sigma}^2}, \tag{A1}$$

where $\sigma = \frac{1}{n(T-1)} S_1(\hat{\gamma})$. Hansen (1999) shows that this statistics follows the distribution function $\Pr(LR_1(\gamma) \leq x) = (1 - exp(-x/2))^2$, with inverse function $c(\alpha) = -2\ln(1 - \sqrt{(1-\alpha)})$, where α is the chosen critical probability value at which one fails to reject the null H_0. For example, the null hypothesis is rejected at the 5% level when the LR statistics exceeds $c(\alpha = .05) = 7.35$. To form a confidence interval for γ, the no-rejection region of the $(1-\alpha)$ confidence level is the set of values for which $LR_1(\gamma) \leq c(\alpha = 0.05)$. This is done by plotting the $LR_1(\gamma)$ and drawing a flat line at $c(\alpha = 0.05)$ (see Hansen 1999, pages 351-352).

In the two- and three-threshold models, the likelihood ratio statistics reads, respectively:

$$LR_2(\gamma) = \frac{S_2(\gamma_2) - S_2(\hat{\gamma_2})}{\hat{\sigma}^2}. \tag{A2}$$

and

$$LR_3(\gamma) = \frac{S_3(\gamma_3) - S_3(\hat{\gamma_3})}{\hat{\sigma}^2}. \tag{A3}$$

Appendix B. Threshold variable, policy variables and controls

B.1 Threshold variable: computation of the knowledge stocks

The threshold variable is then defined as the ratio between the knowledge stocks for renewable over the knowledge stock for fossil energy innovations for each country and each year. To compute the stock variables, we rely on the perpetual inventory method to compute knowledge stocks in renewables and fossil fuel technologies as follows:

$$K_{i,s,t} = PAT_{i,s,t} + (1 - \delta)K_{i,s,t-1} \tag{B4}$$

where s corresponds to either renewable energy or fossil-based technologies and $\delta = 0.1$ is the depreciation rate set at a level in line with the literature on innovation (Peri 2005). The initial value of the knowledge stock is defined as $K_0 = \frac{PAT_{i,s,t_0}}{(\bar{g}_s+\delta)}$, with $\bar{g}_s$ being the average rate of growth of patenting in the technology s for the period between t_0 and $t_0 - 4$. We use $t_0 = 1984$ as the initial year to compute knowledge stock. The first row of Figure 2 shows the evolution of our threshold variable over time. We observe that the threshold variable increased significantly in the BRIICS over the sample period, while in the top OECD countries, this variable displays more of a U-shape. For the latter, note that the upward trends initiate between 2000 and 2005, which is when the Kyoto agreement was to be implemented.

B.2 Policy Variables

Our policy proxies are sourced from the OECD EPS databse, which is the largest country-specific and internationally-comparable database, including information on 14 environmental policy instruments primarily related to climate and air pollution and covering the years 1990-2012 for the countries in our sample. The databases covers both market-based and non-market based instruments. Within the former, it reports information about Taxes (CO_2, Diesel, NO_x and SO_2), Traditing Schemes (Green Certificates, CO_2 and White Certificates), Feed-in Tariffs (Wind and Solar). Within the latter, it reports information on Standards (emission limites for NO_x, SO_2, PMs and diesel sulphur content), and R&D subsidies (Renewable energy public RD&D budget). Stringency is defined as the degree to which environmental policies put an explicit or implicit price on polluting or environmentally harmful behavior. For each policy instruments, countries are scored on a scale from 0 (not stringent) to 6 (highest degree of stringency). For the purpose of our analysis, we create and indicator for CC and one for MB policies, measuring the stringency of market-based and command-and-control policies, respectively. MB is calcuated as the weighted average of (a) taxes on CO_2, NOx and SO_x; (b) trading schemes (Green Certificates, White Certificates and CO_2); and (c) feed-in tariffs (for wind and solar power generation). CC is calculated as the weighted average of the scores for emission limits of NOx, SO_x and PM. These variables are presented in the second and third row of Figure 2. Note that command-and-control policies are vastly adopted in developed countries, while the score is lower and displays less variation in the BRIICS. Market-based policies have a much lower score overall, but their use/stringency increases steadily throughout the sample period, reflecting a gradual replacement of CC policies with MB policies in several countries. Note that in the empirical estimation, we transform the two policy variables so as to make them vary between 0 and 1 by using the following transformation: $\tilde{P}_{it} = \frac{P_{it} - \text{Min}_P}{\text{Max}_P - \text{Min}_P}$, where P stands for either MB or CC policies. We do this in order to facilitate the comparison of the parameter estimates for the two policy instruments.[24]

B.3 Controls

Our estimates are conditional on a vector $\mathbf{X}$ of control variables which are rather standard and include GDP per capita, average years of schooling, the share of electricity and heat exports over total electricity production and Coal Dependence. GDP per capita, defined as the output-side real GDP at chained PPPs in million 2011 USD, is obtained from the Penn Tables (Feenstra et al. 2015) and controls for time-varying, country-specific, macro-economic shocks that could likely affect our dependent variable. We also extract from the Penn Tables a human capital index, defined as the average years of schooling in the population.[25] We claim that a higher educational attainment should make the population of the country more inclined to renewable energy and more generally to environmental issues. The share of electricity and heat exports over total electricity production in a given country and Coal dependence are control variables specific to the energy sector. The former is built using data on exports and production from IEA (2016) and controls for the ability of countries to export electricity to neighbours. This is an important aspect of the energy system because, as discussed more in detail in Verdolini et al. (2016), it provides a buffer to handle the intermittency of renewable electricity generation. Such flexibility would affect our dependent variable because it makes innovation in renewables relatively more attractive. The latter is defined as the sum of coal, gas and oil rents measured as share of GDP, as provided by the World Development Indicators, and controls for the strength and relevance of the fossil fuel sector in a given economy, which can affect both innovation dynamics and the propensity to adopt environmental and energy policies.

[24] Importantly, this transformation does not affect the covariance of either the dependent variable or the set of control variables with the two policy variables.

[25] We refer the reader to the above-mentioned paper Feenstra et al. (2015) and to the documentation attached to the new Penn World Tables proposed by the Groningen Growth and Development Centre (`http://www.rug.nl/ggdc/productivity/pwt/`).

Appendix C. Instrumental Variable Method. Results on the first and second stages with no threshold effect.

Table C1: Results on the second and first stages of the instrumental variables

VARIABLES	(C1) OLS IV 2^{nd} stage	(C2) OLS IV 1^{st} stage MB	(C3) OLS IV 1^{st} stage CC
Pre-sample mean	-0.028	0.093***	-0.033**
	(0.084)	(0.016)	(0.017)
$K_{R/F}$	0.288***	-0.008	0.003
	(0.0418)	(0.008)	(0.010)
$PM2.5$ Counterfactual		0.005***	0.004***
		(0.000)	(0.000)
Length of Democracy		-0.001**	0.002***
		(0.000)	(0.000)
MB policies	1.346**		
	(0.577)		
CC policies	1.494***		
	(0.564)		
GDP per capita	-0.038	0.114***	0.082***
	(0.079)	(0.016)	(0.019)
Coal Dependence	0.048	-0.038**	-0.108***
	(0.104)	(0.015)	(0.0141)
Electricity Exports	1.638***	0.110	-0.209***
	(0.338)	(0.067)	(0.0751)
Human Capital	0.057	-0.019	-0.046**
	(0.089)	(0.018)	(0.022)
Total Knowledge Stock	0.092***	-0.019***	0.016**
	(0.030)	(0.006)	(0.006)
Observations	782	782	782
R-squared	0.535	0.570	0.451
F-Test on excluded Instruments		37.790	29.698

Columns 2 and 3 of Table C1 display the results of the first stage of the IV procedure where both MB and CCg policies are being instrumented by the series of exogenous variables $\mathbf{X}$ in equation 3 and the two additional instruments, length of democracy and $PM2.5$ counterfactual, as exclusion restrictions. The first column of Table C1 presents the second stage of the IV procedure estimating equation 1.

Figure 1: Evolution of renewable patent counts P_{REN}, of fossil fuel patents counts P_{FFS}, and of the ratio of the two patent counts ($P_{R/F}$) for selected OECD and BRIICS countries

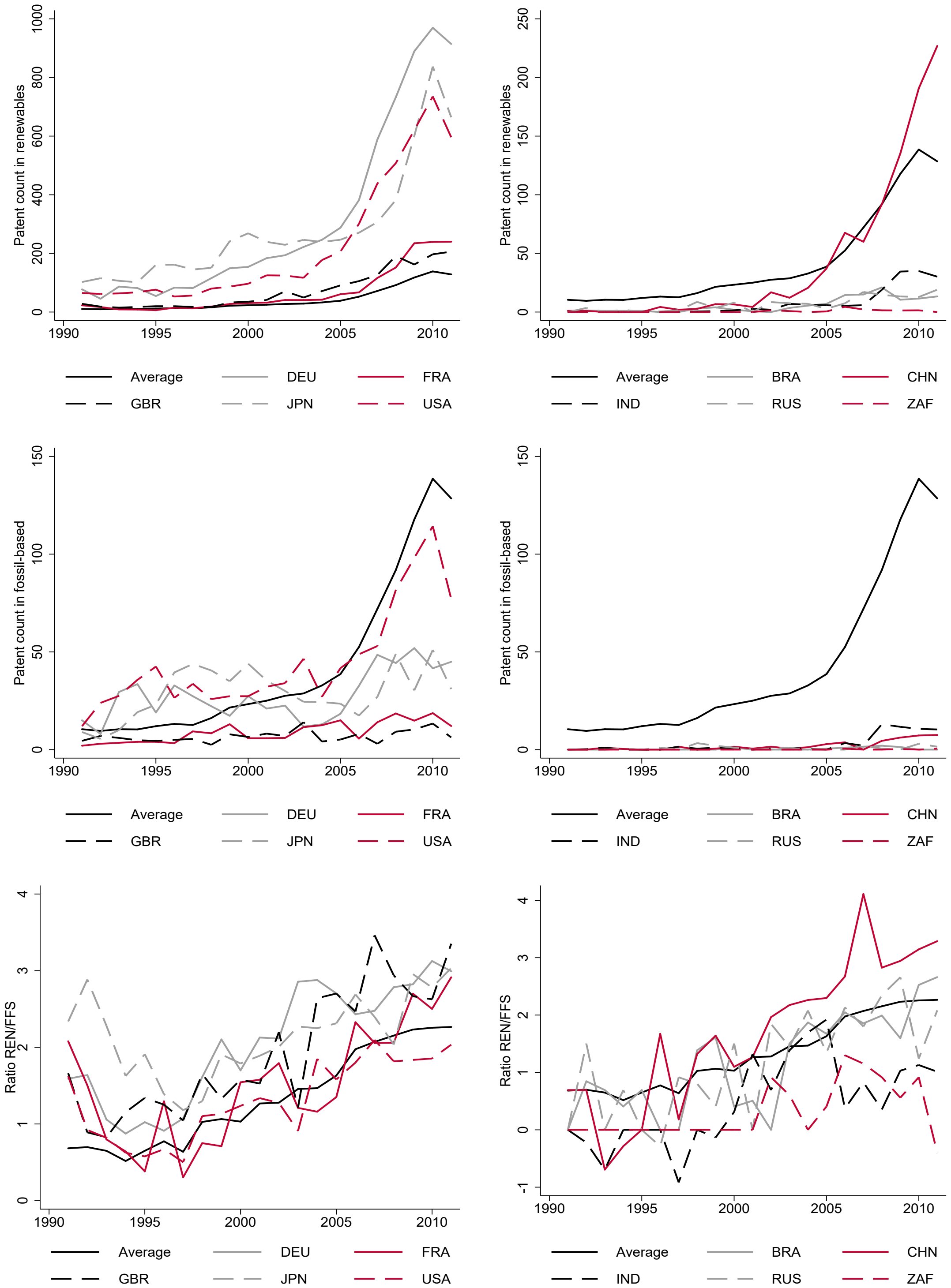

Figure 2: Evolution of the threshold variable and of MB and CC policy scores for selected OECD and for BRIICS countries

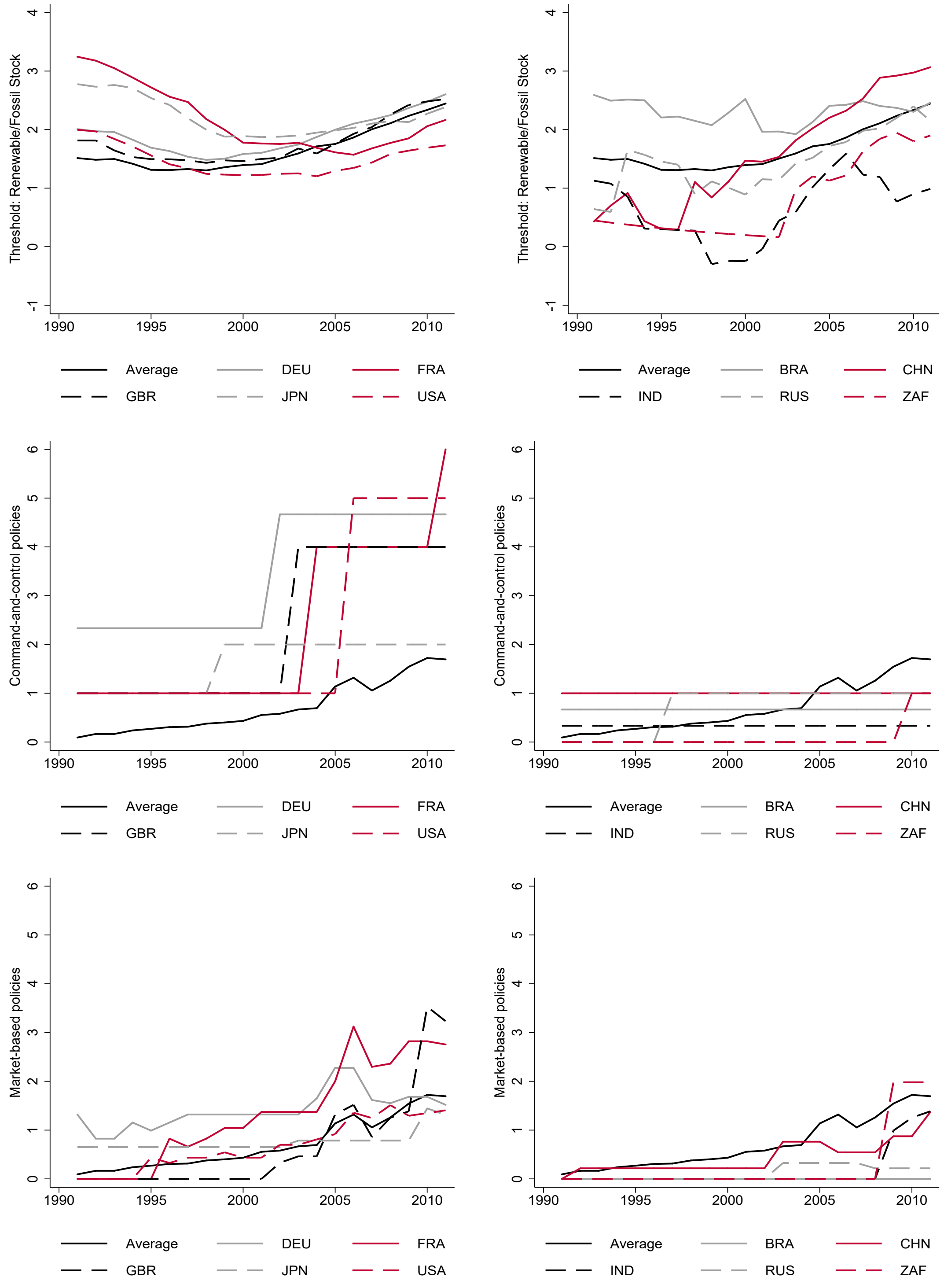

Figure 3: Likelihood Ratio test and confidence interval construction for the three thresholds tested. Vertical axis: LR-test; horizontal axis: percentiles of the threshold variable $K_{R/F}$. The dashed horizontal line represents the 5% critical value of the test.

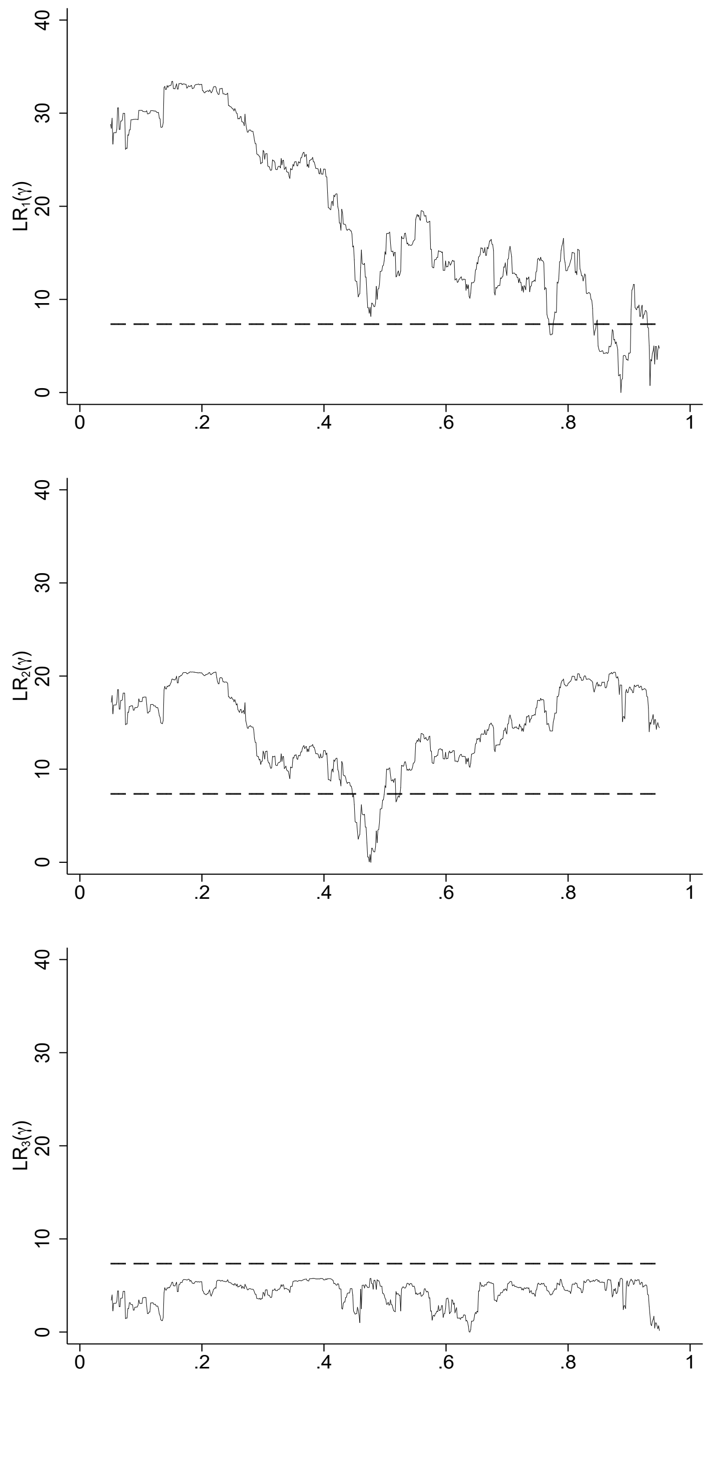

Figure 4: Marginal effect of market-based policies (left panel) and command-and-control policies (right panel) on the ratio of renewable over fossil fuel patents ($P_{R/F}$, top panel), the number of renewable patents (P_{REN}, middle panel) and the number of fossil fuel patents (P_{FFS}, bottom panel). Marginal effects have been computed using a one-standard-deviation change in the policy variable. Vertical axis: Marginal effect from models 5 (top panel), 6 (middle panel) and 7 displayed in Table 5 ; horizontal axis: percentiles of the threshold variables. Dashed lines denote non-significance at 10% level

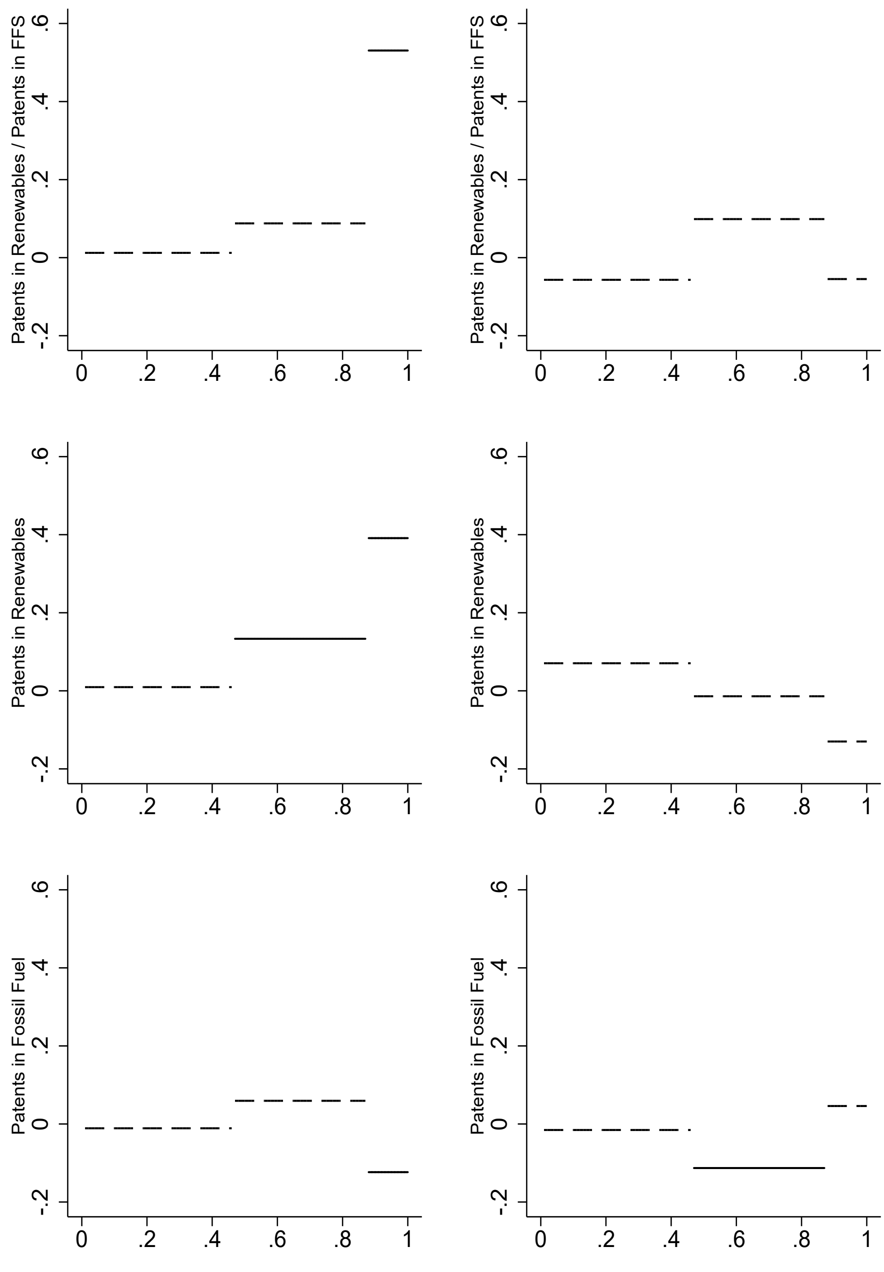

Table 1: Summary statistics

Variable	Name	Obs.	Mean	Median	SD	Min	Max
Renewable/Fossil patents (log)	$P_{R/F}$	782	1.319	1.298	1.043	-1.872	4.839
Renewable patents	P_{REN}	782	42.720	7.000	111.7	0.0	969.6
Fossil patents	P_{FFS}	782	4.753	0.515	11.89	0.0	132.3
Pre-Sample Mean (log)	PSM	782	0.919	0.593	0.768	0.0	2.838
Renewable/Fossil stocks (log)	$K_{R/F}$	782	1.693	1.756	0.819	-0.613	3.995
Market-based policies	MB	833	0.759	0.462	0.846	0.0	3.531
Command-and-Control policies	CC	833	1.940	1.000	1.734	0.0	6.0
GDP per capita (2011 USD PPP)	GDP	850	9.964	10.17	0.733	7.177	11.34
Human Capital	HC	850	2.971	3.113	0.536	1.487	3.734
Total Knowledge Stock	TKS	782	31,262	4,543	71,637	14.35	430,998
Coal Dependence	CD	844	0.136	0.0	0.483	0.0	6.660
Electricity Exports	EE	782	-0.065	-0.029	0.099	-0.573	0.0
Counterfactual $PM2.5_{i,t}$	$INST1$	850	23.31	23.22	9.002	7.677	46.61
Length of Democracy $t-2$	$INST2$	766	37.46	28.0	27.66	1.0	80.0

[a] Electricity Exports is the log of the ratio of electricity exports over production of electricity.

Table 2: Summary statistics by country (Average over the period 1990-2015)

Country	$P_{R/F}$	P_{REN}	P_{FFS}	PSM	$K_{R/F}$	MB	CC	GDP	HC	TKS	CD	EE	$INST1$	$INST2$
ALL	1.32	42.72	4.75	0.92	1.69	0.76	1.94	9.96	2.971	31.26	13.60	-0.065	23.3	37
AUS	1.66	9.46	0.69	1.08	2.31	0.70	1.85	10.50	3.474	5.83	30.50	0.000	8.9	69
AUT	1.86	22.28	1.97	1.39	2.01	1.04	3.67	10.43	3.15	10.92	0.00	-0.170	27.2	45
BEL	1.79	11.81	0.67	1.77	2.44	0.34	2.70	10.32	2.986	7.19	0.00	-0.086	30.1	69
BRA	1.13	5.25	0.33	0.53	2.34	0.00	0.67	9.15	2.159	1.53	0.15	-0.001	11.6	10
CAN	1.82	23.94	2.15	1.61	1.99	1.15	2.64	10.50	3.517	16.82	3.15	-0.070	13.1	69
CHE	1.23	20.91	5.04	1.82	1.46	0.65	2.55	10.68	3.557	16.16	0.00	-0.426	25.2	69
CHN	1.69	44.17	1.87	0.25	1.61	0.57	1.53	8.55	2.192	14.30	80.70	-0.003	43.5	7
CZE	1.15	3.43	0.07	0.00	2.22	0.92	1.91	10.00	3.506	1.07	7.19	-0.147	32.9	11
DEU	2.01	313.00	28.48	1.48	1.95	1.29	3.74	10.44	3.57	178.82	0.80	-0.065	30.5	51
DNK	2.21	37.39	1.13	1.30	2.15	1.47	2.26	10.45	3.317	4.61	0.00	-0.130	19.2	69
ESP	2.36	37.11	0.96	1.44	2.75	1.57	2.15	10.15	2.665	6.54	0.34	-0.036	19.4	22
FIN	1.12	14.81	3.71	0.59	0.74	0.28	3.20	10.35	3.178	10.10	0.00	-0.016	10.0	69
FRA	1.54	69.73	8.85	2.68	2.24	1.45	2.77	10.34	2.942	63.92	0.00	-0.118	24.2	69
GBR	1.94	72.41	6.62	1.65	1.82	1.02	2.73	10.38	3.516	52.25	0.73	-0.003	20.7	69
GRC	1.12	3.64	0.17	0.56	1.84	1.22	1.45	10.04	2.775	0.52	0.63	-0.030	24.7	25
HUN	0.99	2.41	0.07	0.65	1.71	0.91	1.87	9.69	3.051	1.79	0.30	-0.094	33.4	11
IDN	0.14	0.21	0.00	0.00	0.30	0.29	0.94	8.46	2.202	0.09	58.60	0.000	25.2	14
IND	0.44	7.37	3.05	0.42	0.68	0.36	0.44	7.81	1.786	2.54	54.00	0.000	37.8	10
IRL	1.02	4.37	0.13	0.50	1.95	0.26	2.04	10.47	2.901	1.40	0.03	-0.004	13.8	69
ITA	1.61	53.98	5.88	1.54	1.82	1.32	2.39	10.35	2.816	32.10	0.00	-0.004	31.2	23
JPN	2.16	274.40	28.35	2.84	2.26	0.98	1.65	10.42	3.37	316.79	0.00	0.000	20.0	23
KOR	1.99	119.50	5.11	0.59	2.05	1.06	2.51	10.06	3.231	48.74	0.30	0.000	38.7	12
MEX	0.63	1.41	0.00	0.05	0.84	0.01	0.85	9.41	2.444	0.59	1.35	-0.007	17.9	6
NLD	2.16	27.92	1.93	1.73	2.26	0.82	2.28	10.50	3.165	15.13	0.00	-0.031	30.2	69
NOR	1.77	15.09	1.34	0.47	1.73	0.42	2.35	10.83	3.406	3.67	0.66	-0.081	10.2	69
POL	0.79	4.34	0.59	0.55	1.62	0.96	1.88	9.55	3.049	0.87	23.50	-0.041	31.2	10
PRT	1.12	3.65	0.10	0.41	2.17	1.13	2.17	9.93	2.21	0.36	0.00	-0.061	15.4	23
RUS	1.18	6.49	0.71	0.10	1.46	0.13	0.73	9.56	3.113	2.70	60.50	-0.009	19.4	8
SVK	0.65	1.43	0.09	0.05	1.39	0.67	0.57	9.71	3.386	0.34	0.16	-0.162	32.0	10
SVN	0.39	0.91	0.11	0.10	0.94	0.38	1.87	9.97	3.282	0.46	2.19	-0.308	25.5	10
SWE	1.02	15.97	3.94	1.28	1.26	1.20	2.06	10.45	3.238	18.81	0.00	-0.072	12.3	69
TUR	0.60	1.74	0.11	0.00	0.89	0.39	1.15	9.45	2.04	0.44	0.88	-0.007	24.0	15
USA	1.28	221.10	47.34	1.65	1.53	0.78	2.64	10.71	3.596	225.09	6.24	-0.004	18.7	69
ZAF	0.29	0.62	0.06	0.18	0.83	0.23	0.23	9.17	2.221	0.45	125.10	-0.033	14.6	12

$P_{R/F}$: Renewable over fossil fuels patent count ratio; P_{REN}: Number of patents in renewables; P_{FFS} : Number of patents in fossil fuels; PSM: Pre-sample mean of the dependent variable $P_{R/F}$; $K_{R/F}$: Renewable over fossil fuels patent stock ratio; MB: Markat based policies; CC: command-and-control policies; GDP: GDP per capita, in thousands of 2011 USD PPP; HC: Human capital index; TPS: total patent stock (in thousands); CD: Coal dependence ($\times 10^2$); EE: Electricity export; INS1: particular matter $PM2.5_{i,t}$; INS2 democracy longevity (in years).

Table 3: Sequential Regressions. Dependent Variable: (Log of the) Ratio of renewable to fossil fuel patents ($P_{R/F,it}$)

	(1)	(2)	(3)	(4)
Pre-Sample Mean	0.386***	0.315***	0.026	-0.001
	(0.090)	(0.095)	(0.144)	(0.131)
$K_{R/F}$	0.353***	0.338***	0.294***	0.106
	(0.076)	(0.070)	(0.081)	(0.065)
MB Policies		0.388	0.456*	-1.497***
		(0.264)	(0.258)	(0.462)
MB $\times K_{R/F}$				0.951***
				(0.255)
CC Policies		0.464*	0.266	-0.350
		(0.252)	(0.183)	(0.313)
CC $\times K_{R/F}$				0.224
				(0.149)
GDP per capita			0.100	0.151
			(0.099)	(0.094)
Coal Dependence			-0.130	-0.100
			(0.108)	(0.100)
Electricity Exports			1.265**	0.910**
			(0.465)	(0.403)
Human Capital			0.026	-0.005
			(0.143)	(0.120)
Total Knowledge Stock			0.110*	0.147**
			(0.063)	(0.058)
Observations	782	782	782	782
R-squared	0.547	0.561	0.602	0.628
LL	-832.5	-820.4	-781.9	-754.9
RSS	385	373.2	338.3	315.7
LR-test		24.26	76.89	54.05
P-value		0.000	0.000	0.000

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a full vector of unreported year fixed effects. All LR-tests compare the current specification (m) with specification$(m-1)$.

Table 4: Threshold percentile, value, and significance test for the threshold variable (log of) $K_{R/F}$

	$\hat{\gamma}_1$	$\hat{\gamma}_2$	$\hat{\gamma}_3$
Threshold percentile	88	47	64
Threshold value for $K_{R/F}$	2.856	1.706	2.004
95 % CI for $K_{R/F}$	[2.483, 2.678]	[1.664, 1.757]	[NA, NA]
F-statistics	33.03	19.68	5.873
P-value	0.000	0.094	0.736

The obtained thresholds are estimated from model 5 of Table 3 with 500 bootstrapped samples. See Appendix A about inference of the estimated thresholds and on the determination of their confidence intervals.

Table 5: Threshold regressions using as the dependent variable the log of ratio of renewable over fossil fuel patents ($P_{R/F}$), the number of renewable patents (P_{REN}) and the number of fossil fuel patents (P_{FFS}), respectively

	$P_{R/F}$ [a] (5)	P_{REN} (6)	P_{FFS} (7)
Pre-Sample Mean	0.006	0.099	0.456***
	(0.128)	(0.114)	(0.125)
$K_{R/F}$	0.134*	0.416***	0.350***
	(0.066)	(0.103)	(0.065)
MB $\times \mathbf{I}(K \leq \hat{\gamma}_2)$	0.053	0.041	-0.047
	(-0.293)	(-0.362)	(-0.294)
MB $\times \mathbf{I}(\hat{\gamma}_2 < K \leq \hat{\gamma}_1)$	0.377	0.572**	0.255
	(-0.299)	(-0.252)	(-0.235)
MB $\times \mathbf{I}(K \leq \hat{\gamma}_1)$	2.276***	1.678***	-0.529
	(-0.592)	(-0.535)	(-0.327)
CC $\times \mathbf{I}(K \leq \hat{\gamma}_2)$	-0.207	0.258	-0.056
	(-0.214)	(-0.234)	(-0.238)
CC $\times \mathbf{I}(\hat{\gamma}_2 < K \leq \hat{\gamma}_1)$	0.361	-0.051	-0.412**
	(-0.247)	(-0.242)	(-0.164)
CC $\times \mathbf{I}(K \geq \hat{\gamma}_1)$	-0.2	-0.474	0.168
	(-0.384)	(-0.393)	(-0.255)
GDP per capita	0.141	-0.138	-0.131
	(0.094)	(0.123)	(0.081)
Coal Dependence	-0.120	-0.139	0.009
	(0.093)	(0.109)	(0.057)
Electricity Exports	0.949**	1.261**	-0.118
	(0.395)	(0.542)	(0.374)
Human Capital	0.016	0.114	-0.037
	(0.124)	(0.155)	(0.104)
Total Knowledge Stock	0.139**	0.220**	0.087*
	(0.058)	(0.087)	(0.044)
Observations	782	782	782
R-squared	0.631	0.881	0.802
LL	-752.1	-689.8	-558.6
RSS	313.4	267.3	191.1
LR-test	5.626		
P-value	0.060		

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a full vector of unreported year fixed effects. Variable K stands for $K_{R/F}$ in model 5, K_{REN} in model 6 and K_{FFS} in model 7. Percentile values of the two thresholds are $\hat{\gamma}_1 = .88$ and $\hat{\gamma}_2 = .47$ (see Table 4).

[a] The LR-test compares model 4 from Table 3 with model 5.

Table 6: Robustness tests using various specifications for the threshold regressions.

	(5)	(8)	(9)	(10)	(11)
Pre-Sample Mean	0.006	-0.047	-0.079	-0.031	0.505***
	(0.128)	(0.139)	(0.128)	(0.117)	(0.110)
$K_{R/F}$	0.134*	0.115*	0.204***	0.131**	-0.037
	(0.066)	(0.063)	(0.063)	(0.057)	(0.144)
MB 1^{st} regime	0.052	0.623	-0.126	0.007	-0.408
	(0.293)	(0.784)	(0.231)	(0.344)	(0.608)
MB 2^{nd} regime	0.376	0.780	0.909***	0.463	-0.079
	(0.300)	(0.921)	(0.316)	(0.286)	(0.476)
MB 3^{rd} regime	2.276***	7.015***	2.478***	1.550*	1.895**
	(0.591)	(1.742)	(0.377)	(0.766)	(0.914)
CC 1^{st} regime	-0.204	0.966	0.005	-0.008	0.305
	(0.211)	(0.898)	(0.211)	(0.259)	(0.402)
CC 2^{nd} regime	0.362	1.801*	-0.036	0.401	0.629**
	(0.247)	(1.022)	(0.233)	(0.265)	(0.278)
CC 3^{rd} regime	-0.199	-2.360	-0.168	0.568	-0.481
	(0.384)	(1.400)	(0.407)	(0.557)	(0.643)
GDP per capita	0.141	0.049	0.093	0.226***	0.348
	(0.094)	(0.115)	(0.095)	(0.079)	(0.237)
Coal Dependence	-0.120	0.029	-0.138*	-0.108	-0.230**
	(0.093)	(0.123)	(0.069)	(0.098)	(0.100)
Electricity Exports	0.949**	1.150**	0.858**	0.839*	-1.494
	(0.395)	(0.431)	(0.396)	(0.433)	(1.082)
Human Capital	0.016	0.044	0.092	-0.046	-0.466
	(0.124)	(0.127)	(0.075)	(0.106)	(0.338)
Total Knowledge Stock	0.139**	0.117**	0.134***	0.124**	
	(0.058)	(0.054)	(0.049)	(0.050)	
Total Primary Energy Supply					-0.006
					(0.074)
First Threshold	88	89	94	87	88
P-value first threshold	0.000	0.002	0.008	0.006	*given*
Second Threshold	47	48	65	57	47
P-value second threshold	0.094	0.022	0.052	0.076	*given*
Third Threshold	64	11	13	10	-
P-value third threshold	0.736	0.448	0.446	0.440	-
Observations	782	782	782	782	782
R-squared	0.631	0.634	0.650	0.633	0.693
LL	-752.1	-748.9	-731.2	-750.5	-788.7
RSS	313.4	310.8	297.1	312.1	344.1

Clustered standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a full vector of unreported year fixed effects. In Models 5 through 10 the dependent variable is the (log of the) ratio of renewable over fossil fuel patents ($P_{R/F}$). Model 5 is displayed in Table 3. Model 8 uses instrumental variables (IV) to control for the endogeneity of the two policy variables. The results for the first stage are displayed in Appendix C. Model 9 only counts patents protected in at least 4 countries. Model 10 uses a broader definition of renewable patents. Finally, Model 11 uses the share of renewable energy generation in country as a depedent variable.

Table 7: Percentile values of the threshold variable of renewable over fossil fuel patent stocks ($K_{R/F}$), market-based policy index, and command-and-control policy index by country and by subperiods

	$K_{R/F}$ 1990-2012	MB 1990-2012	CC 1990-2012	$K_{R/F}$ P1[a]	$K_{R/F}$ P2[b]	$K_{R/F}$ P3[c]	MB P1	MB P2	MB P3	CC P1	CC P2	CC P3
ALL	50.20	0.21	0.31	41.89	45.54	72.40	0.06	0.20	0.44	0.13	0.32	0.56
AUS	75.83	0.15	0.25	69.50	73.40	90.80	0.00	0.12	0.44	0.00	0.22	0.72
AUT	63.30	0.29	0.61	59.25	58.20	80.00	0.08	0.39	0.44	0.61	0.61	0.61
BEL	79.61	0.10	0.45	72.38	77.50	95.40	0.00	0.08	0.28	0.17	0.46	0.89
BRA	78.48	0.00	0.11	82.25	73.40	82.60	0.00	0.00	0.00	0.11	0.11	0.11
CAN	62.09	0.26	0.37	55.38	58.10	80.80	0.05	0.16	0.82	0.00	0.34	1.00
CHE	36.43	0.18	0.43	54.63	21.30	37.60	0.00	0.11	0.62	0.39	0.39	0.56
CHN	46.65	0.13	0.19	11.88	49.90	95.80	0.05	0.13	0.29	0.15	0.17	0.29
CZE	72.30	0.26	0.32	44.63	83.40	94.40	0.06	0.26	0.59	0.00	0.40	0.67
DEU	59.52	0.38	0.58	55.00	50.90	84.00	0.27	0.45	0.43	0.39	0.62	0.78
DNK	63.91	0.42	0.38	41.25	65.70	96.60	0.21	0.45	0.69	0.15	0.42	0.67
ESP	85.17	0.45	0.36	81.13	81.20	99.60	0.14	0.63	0.57	0.15	0.37	0.67
FIN	16.96	0.08	0.53	8.38	13.80	37.00	0.00	0.05	0.27	0.35	0.59	0.72
FRA	69.04	0.38	0.39	93.88	51.50	64.40	0.05	0.45	0.75	0.17	0.37	0.80
GBR	52.52	0.21	0.38	44.00	43.50	84.20	0.00	0.14	0.70	0.17	0.42	0.67
GRC	52.00	0.35	0.24	37.88	41.30	96.00	0.19	0.36	0.57	0.10	0.25	0.44
HUN	49.95	0.27	0.33	25.86	51.60	80.40	0.00	0.31	0.57	0.00	0.38	0.67
IDN	8.44	0.05	0.16	2.00	3.10	29.40	0.00	0.00	0.22	0.13	0.17	0.17
IND	14.65	0.06	0.06	13.63	14.10	17.40	0.00	0.00	0.29	0.06	0.06	0.06
IRL	54.87	0.07	0.34	22.00	59.10	99.00	0.00	0.06	0.21	0.04	0.42	0.67
ITA	53.22	0.34	0.32	61.13	39.00	69.00	0.18	0.34	0.59	0.17	0.27	0.67
JPN	73.74	0.24	0.27	88.50	60.50	76.60	0.19	0.20	0.38	0.17	0.32	0.33
KOR	61.43	0.30	0.38	72.25	38.90	89.20	0.00	0.39	0.59	0.17	0.37	0.72
MEX	28.61	0.00	0.14	1.00	21.90	86.20	0.00	0.00	0.00	0.08	0.17	0.17
NLD	72.43	0.23	0.38	61.88	69.40	95.40	0.00	0.21	0.65	0.17	0.35	0.78
NOR	49.83	0.12	0.39	39.25	43.20	80.00	0.00	0.07	0.42	0.13	0.47	0.67
POL	45.26	0.27	0.31	49.00	31.70	66.40	0.09	0.27	0.56	0.11	0.30	0.67
PRT	67.61	0.32	0.36	38.25	78.90	92.00	0.15	0.39	0.46	0.10	0.42	0.67
RUS	39.00	0.03	0.12	24.88	33.10	73.40	0.00	0.05	0.06	0.02	0.17	0.17
SVK	39.61	0.19	0.09	12.88	49.00	63.60	0.05	0.18	0.45	0.00	0.13	0.17
SVN	21.89	0.14	0.39	12.67	21.00	29.20	0.01	0.07	0.35	0.17	0.32	0.67
SWE	26.87	0.34	0.34	27.13	21.50	37.20	0.14	0.37	0.60	0.00	0.46	0.67
TUR	24.91	0.10	0.13	2.00	26.30	58.80	0.00	0.07	0.31	0.00	0.07	0.47
USA	38.91	0.20	0.37	49.50	26.70	46.40	0.04	0.22	0.40	0.17	0.30	0.86
ZAF	21.65	0.07	0.02	9.00	16.20	52.80	0.00	0.00	0.34	0.00	0.00	0.10

[a] Average for the period 1990-1997
[b] Average for the period 1998-2007
[c] Average for the period 2008-2012