ENVIRONMENTAL POLICY CHOICE AND THE DIRECTION OF INNOVATION

Lionel Nesta

Elena Verdolini

Francesco Vona

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CONTACT US

OFCE
10 place de Catalogne | 75014 Paris | France
Tél. +33 1 44 18 54 24
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ABOUT THE AUTHORS

Lionel Nesta, Université Côte d'Azur, CNRS, GREDEG, OFCE-Sciences Po and SKEMA Business School, France.
Email Address: lionel.nesta@univ-cotedazur.fr
Elena Verdolini, Universita degli Studi di Brescia and RFF-CMCC European Institute on Economics and the Environment, Euro-Mediterranean Center on Climate Change, Italy.
Email Address: elena.verdolini@unibs.it
Francesco Vona, Universita di Milano, Italy and Fondazione Eni Enrico Mattei, Italy.
Email Address: francesco.vona@unimi.it

ABSTRACT

This paper analyses how policy choice affects the direction of innovation towards renewable and away from fossil-fuel energy technologies in a sample of 33 countries between 1990 and 2012. By policy choice, we mean the combination of market-based and command-and-control policy instruments. We develop three competing models of energy innovation – the linear, the interaction and the threshold models – and show that the threshold model is the best fit for the data. We then simulate the direction of innovation over the sample period under various policy scenarios. We show that under the appropriate policy mix, countries can swiftly break out from fossil fuel towards renewable energy innovation.

KEYWORDS

Energy Innovation, Policy Instrument Choice, Technological Transition, Discontinuities, Simulation.

JEL

O3, O38, Q4, Q48, Q55.

Environmental Policy Choice and the Direction of Innovation*

Lionel Nesta[†] Elena Verdolini[‡] Francesco Vona[§]

Abstract

This paper analyses how policy choice affects the direction of innovation towards renewable and away from fossil-fuel energy technologies in a sample of 33 countries between 1990 and 2012. By policy choice, we mean the combination of market-based and command-and-control policy instruments. We develop three competing models of energy innovation – the linear, the interaction and the threshold models – and show that the threshold model is the best fit for the data. We then simulate the direction of innovation over the sample period under various policy scenarios. We show that under the appropriate policy mix, countries can swiftly break out from fossil fuel towards renewable energy innovation.

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†Université Côte d'Azur, CNRS, GREDEG, OFCE SciencesPo and SKEMA Business School, France. lionel.nesta@univ-cotedazur.fr

‡Università degli Studi di Brescia and RFF-CMCC European Institute on Economics and the Environment, Euro-Mediterranean Center on Climate Change, Italy. elena.verdolini@unibs.it

§Università di Milano, Italy, and Fondazione Eni Enrico Mattei, Italy. francesco.vona@unimi.it

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JEL classification: O3; O38; Q4; Q48; Q55

1 Introduction

This paper analyses the effectiveness of environmental policies portfolios in directing innovation towards renewable energy sources and away from fossil fuels. By policy portfolios, we mean the choice between, and the combination of, market-based policies and command-and-control policies, which has attracted much attention in the environmental economics literature (Weitzman 1974, Hahn & Stavins 1992, Requate 2005, Nordhaus 2019). Our intuition is that policy effectiveness – and the direction of innovation induced by such policies – depends on the accumulation of technological competencies in the new technology *vis-à-vis* the incumbent one. Building on the literature about directed technical change (Acemoglu et al. 2012, Noailly & Smeets 2015, Aghion et al. 2016), we argue that the *choice* of optimal policies is specific to the degree of specialization in renewable technologies relative to fossil fuel ones.

We develop three competing models of the direction of energy innovation. Each model implies a specific channel through which heterogeneous policies translate into energy innovation. The *linear* model assumes that policy effectiveness applies uniformly, irrespective of the countries' capabilities in the two competing technologies. The *interaction* model allows for policy effectiveness to change gradually with such capabilities. The *threshold* model gives room for discontinuities in policy effectiveness depending on the level of capabilities. Using country-level data, we estimate these three models and choose the one that best fits the country level data. Based on our preferred model, we quantify policy effectiveness by comparing the observed policy scenario with two counterfactual scenarios in which countries choose the appropriate policy instruments at various levels of stringency.

Our results can be summarized as follows. First, the threshold model, which shows strong discontinuities in policy effectiveness to direct innovation, is the one that best fits historical data. Second, policy effectiveness depends on the countries' (relative) capabilities in the two competing technologies, i.e., renewables and fossil-fuel technologies. Third, the *choice* of the optimal policy instrument mix *also* depends on the level of technological specialization. Breaking out from the dominant technology when the relative specialization in the novel technology is very low requires the use of command-and-control policies. Market-based policies are effective in redirecting innovation only if a country has a sufficiently high level of specialization in such technologies. Fourth, our simulations show that, if the choice of policies is timed correctly, countries can break out from a dominant technology in a relatively swift period of time.

The remainder of the paper is organized as follows. Section 2 positions our contribution in the existing literature. Section 3 presents the conceptual framework which motivates our empirical analysis, and Section 4 addresses the various challenges of our econometric implementation. Section 5 discusses empirical results and simulates how optimal policy choice, timing, and stringency affect policy effectiveness. Section 6 concludes.

2 Literature review

The main intuition of this contribution is that the appropriate policy choice to promote the technological transition towards renewable energy (a new technology) and away from fossil fuels (an incumbent technology) is contingent on the stage of technological development of a country. This idea is certainly not new. In particular, the emergence of multiple equilibria and poverty traps has been related to factors – and thus, implicitly, to policies and institutions (Rodrik 2005) – affecting mass consumption (Murphy et al. 1989), the interaction between financial frictions and human capital accumulation (Galor & Zeira 1993) or technical skills required to pursue an R&D-based growth strategy (Howitt & Mayer-Foulkes 2005). An important contribution is Acemoglu et al. (2006): at early stages of development, growth is favored by an investment-based strategy; conversely, at later stages of development a jump to an innovation-based strategy is required.

To the best of our knowledge, no research has to date tested the hypothesis that policy *effectiveness* in directing innovation away from fossil fuels and towards renewable technologies is conditional upon past knowledge accumulation. On the one hand, the environmental innovation literature shows that past knowledge is a crucial element to understand the dynamics of further technological development (Popp 2002, Verdolini & Galeotti 2011, Noailly & Smeets 2015). On the other hand, environmental policies also play a key role in promoting the break out from an established technological trajectory. In their key contribution, Aghion et al. (2016) build on the directed technical change literature to show that, in the context of path-dependent innovation, firms redirect technical change away from polluting technologies and toward cleaner technologies in response to (policies which) increase the price of fossil energy. Yet, their analysis relies on the key assumption that policy effectiveness on innovation outcomes is not influenced by path dependency.

The first contribution of this paper is to empirically test the assumption of independence between technological specialization resulting from accumulated knowledge and environmental policy effectiveness. While there is no strong prior to assume this assumption holds, past contributions evaluating the causal effect of environmental policies on innovation do not question whether the appropriate policy vector is conditional on past accumulation of knowledge (see, e.g. Popp 2002, Nesta et al. 2014, Calel & Dechezleprêtre 2016, Dugoua 2023). Conversely, our empirical approach allows the effect of a given environmental policy on the direction of innovation to be mediated by a given country's existing competencies.

Consequently, our second contribution is methodological. We develop an empirical protocol to compare three competing models of possible interaction between accumulated technological capabilities and policy effectiveness: (*i*) the linear model, which is most common in prior research, where policy effectiveness is not influenced by technological capabilities; (*ii*) the interaction model, where the influence of accumulated capability on policy effectiveness is smooth and continuous; (*iii*) the threshold model, which allows for sharp discontinuities in policy effectiveness.

Our third contribution is the focus on the simultaneous assessment of the effectiveness of command and control (CC) and market-based (MB) policies in directing innovation towards renewable and away from fossil fuel technologies. Command-and-control instruments regulate either the type of technology adopted or the level of emissions (typically, emission limits or technology standards). Market-based policies price emissions directly or indirectly (typically, feed-in tariffs or emission taxes) (Requate 2005). Only few contributions evaluate both instruments simultaneously (e.g., Lamperti et al. 2020, Aghion et al. 2016), and none allow for policy effectiveness to depend on existing capabilities.

We purposely focus on the "dynamic incentives" provided by command-and-control and market-based environmental policy instruments – that is, their ability to spur innovation and direct it away from fossil-based technologies towards renewable energy options. In doing so, we depart from the prevalent attempts to assess the complementarity or substitution between innovation policies (i.e., R&D investments) and price-based policies such as carbon taxes or permits. Indeed, the role of direct R&D investments inspiring innovation is well-established. Several contributions also compare the effectiveness of green technology policy and carbon taxes (e.g., Greaker et al. 2018, Noailly & Smeets 2015, Aghion & Jaravel 2015).[1] Conversely, the few available modeling and empirical analyses on the differential dynamic incentives provided by market-based *vs.* command-and-control instrument to direct innovation provide conflicting evidence (Requate 2005, Hepburn 2006, Lamperti et al. 2020, Gugler et al. 2024).

We therefore complement the existing literature by proposing a new methodology that allows identifying appropriate environmental policies that effectively redirect innovation in the desired trajectory, depending on relative technological capabilities. Furthermore, our effort to quantify policy effectiveness by means of counterfactual scenarios informs the debate on the appropriate environmental policy choice, its timing and its desired level of stringency.

[1] Greaker et al. (2018) suggest that direct R&D programs are more effective than market-based approaches. More recently, Gugler et al. (2024) show that R&D investments spur green innovation, beyond and above the positive effect of market based policies.

3 Competing models of the direction of technical change[2]

The starting point of our analysis is the aggregate Cobb-Douglas knowledge production: new knowledge k stems from an existing stock of knowledge K, augmented with a policy vector $\mathbf{P}$, whose composition and effects represent the core of our investigation. We consider two technologies, i.e. a new technology that competes with an incumbent one. In the context of energy innovation, renewable technologies g challenge the incumbent, fossil-efficient technology f. This gives rise to one knowledge production function per technological domain.

The presence of two competing technological paradigms naturally raises the issues of policy effectiveness in directing technical change. To account for this, we follow Acemoglu et al. (2012) and focus on the ratio of the two knowledge production function equations: the numerator pertains to field g, and the denominator pertains to field f. Abstracting from country i and time t, this yields the following ratio equation:

$$rk = rA \cdot rK^{\beta_{K_g}} \cdot K_f^{-\beta_{K_f}} \cdot K_{-(g+f)}^{\beta_{K_{-(g+f)}}} \cdot \mathbf{C}^{\mathbf{B_C}} \cdot e^{\mathbf{B_P} \times \mathbf{P} + \epsilon}, \tag{1}$$

where prefix r implies relative values for innovation flows k, constant A and knowledge capital K, such that $rk = k_g/k_f$, $rA = A_g/A_f$, and $rK = K_g/K_f$. The inclusion of knowledge stocks K controls for past R&D investments and incentives in either fields g and f, which have successfully translated into and innovation out-

[2]This Section is based on Appendix A, which provides a more thorough presentation of our modelling strategy.

come, i.e., patents. Equation 1 also introduces overall knowledge stocks $K_{-(g+f)}$, allowing for the presence of spillovers stemming from domains other than fields g and f. Vector C represents a vector of controls and ϵ embodies various shocks discussed in Section 4.

The dependent variable $rk = k_g/k_f$ can be interpreted as the direction of energy innovation in a given country. If rk is larger than unity, innovation in the novel (carbon-free) technological domain – which represents a path-breaking solution to global warming – progresses faster than innovation in the incumbent (carbon-efficient) technological domain – which represents a transitory and incomplete solution to global warming. In a similar fashion, variable $rK = K_g/K_f$ represents the level of accumulated competences accumulated in renewable energy sources relative to those in incumbent fossil fuel energy sources. Higher values of rK imply more specialization towards sustainable growth as opposed to the current paradigm of economic growth.

Taking logs of Equation (1) yields what we refer to as the linear model of directed technical change:

$$\ln rk = \ln rA + \beta_{K_g} \ln rK - \beta_{Kf} \ln K_f + \beta_{K_{-(g+f)}} \ln K_{-(g+f)} + \mathbf{B_C} \ln \mathbf{C} + \mathbf{B_P} \mathbf{P} + \epsilon. \quad (2)$$

The coefficient vector $\mathbf{B_P}$ captures the marginal effect of a unit increase in the stringency of specific environmental policies on the direction of energy innovation. Importantly, this model assumes that policy effectiveness in directing innovation is independent from relative specialization of a country in renewable vs. fossil technologies rK. Model (2) represents the benchmark of our empirical analysis, that is, the null model against which alternative models are being compared.

A straightforward extension of Model (2) is to assume that policy effectiveness is mediated by the relative specialization in the two technological domains. This is obtained by interacting the vector of policy variables $\mathbf{P}$ with the ratio rKA:

$$
\begin{aligned}
\ln rk &= \ln rA + \beta_{K_g} \ln rK + \mathbf{B_P P} + \mathbf{B_{K_g,P}} (\ln rK \times \mathbf{P}) \\
&- \beta_{Kf} \ln K_f + \beta_{K_{-(g+f)}} \ln K_{-(g+f)} + \mathbf{B_C} \ln \mathbf{C} + \epsilon.
\end{aligned} \tag{3}
$$

Model (3) is an unconstrained version of Model (2) where policy effectiveness is not assumed to be constant. Rather, the marginal effect of policy depends linearly on the relative stock of knowledge stock rK.[3] We call this model the interaction model.

A less straightforward extension of Model (2) can be used to search for discontinuities in the mediating effect of specialization on policy effectiveness; that is, to identify whether thresholds exist, in terms of values of rK, below or above which a given policy becomes both effective and stable. Conditional on the existence of a threshold, this model reads:

$$
\begin{gathered}
\ln rk = \ln rA + \beta_{K_g} \ln rK + \mathbf{B_{1P} P} \times \mathbb{1}_1(\gamma) + \mathbf{B_{2P} P} \times \mathbb{1}_2(\gamma) \\
- \beta_{Kf} \ln K_f + \beta_{K_{-(g+f)}} \ln K_{-(g+f)} + \mathbf{B_C} \ln \mathbf{C} + \epsilon,
\end{gathered} \tag{4}
$$

where $\mathbb{1}$ are indicator variables for different regimes of policy effectiveness. Variable

[3]Observe that policy effectiveness now becomes a linear function of relative specialization rK: $\partial \ln rk / \partial \mathbf{P} = \mathbf{B_P} + \mathbf{B_{K_g,P}} \times \ln rK$.

$\mathbb{1}_1$ is set to unity when the threshold variable $\ln rK$ is below γ (i.e. $\ln rK \leq \gamma$), 0 otherwise, and $\mathbb{1}_2$ is set to unity when $\ln rK$ exceeds the given threshold value γ (i.e. $\ln rK > \gamma$), 0 otherwise. Model (4) allows for abrupt variations in the effect of policy on the direction of innovation, depending on the relative degree of specialization. For instance, below the threshold γ, the marginal effect of environmental policies is $\mathbf{B_{1P}}$. We refer to this effect as the policy inducement effect in the "first policy regime", i.e. the regime which includes country-year observations characterized by a relative level of competencies in renewables relative to fossil-based technologies below the identified threshold. In turn, $\mathbf{B_{2P}}$ captures the policy effectiveness in the group of country-year observations with a level of relative competencies above the identified threshold. If Model (4) is preferred over Model (2), we can then search for a second threshold using the two-threshold model, which reads:

$$\begin{aligned} \ln rk = {} & \mathbf{B_{1P}P} \times \mathbb{1}_1(\gamma_1, \gamma_2) + \mathbf{B_{2P}P} \times \mathbb{1}_2(\gamma_1, \gamma_2) + \mathbf{B_{3P}P} \times \mathbb{1}_3(\gamma_1, \gamma_2) \\ & \ln rA + \beta_{K_g} \ln rK - \beta_{Kf'} \ln K_f + \beta_{K_{-(g+f)}} \ln K_{-(g+f)} + \mathbf{B_C} \ln \mathbf{C} + \epsilon, \end{aligned} \tag{5}$$

where $\mathbb{1}_1$ is set to unity when $\ln rK \leq \gamma_1$, 0 otherwise, $\mathbb{1}_2$ is set to unity when $\gamma_1 < \ln rK \leq \gamma_2$, 0 otherwise, and $\mathbb{1}_3$ is set to unity when $\ln rK > \gamma_2$, 0 otherwise.[4] It is straightforward to extend Equation (5) to a higher number of thresholds.

Models (2) to (4)-(5) represent three competing models of the direction of technical chance. The comparison of their explanatory power will allow us to identify the one that best fits the observed data.

[4]For the sake of simplicity, we assume here that $\gamma_1 < \gamma_2$.

4 Empirical protocol

4.1 Data sources

This paper combines patent data, policy data, and economic data. First, we use patent data to construct both the dependent variable – which measures the direction of innovative activity – and the threshold variable – which measures the relative specialization between the two competing technologies. The dependent variable is defined as the ratio of renewable to fossil fuel patents by inventors in country i in year t. The threshold variable, measuring each country's level of specialization in renewables relative to fossil-fuels is defined as the ratio of the patent stock in renewable over the patent stock in fossil-fuel energy, by country-year. The inclusion of knowledge stocks controls for past R&D investments in either fields g and f, which have successfully translated into patents.[5]

Proxies for command-and-control and market-based policy instruments are build using data from the OECD EPS - Environmental Policy Stringency database (Botta & Kozluk 2014). OECD EPS 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

[5]Patent stocks are only an imperfect control for past R&D investments, whether funded and/or performed by public or private research organizations. However, past literature (e.g. Griliches 1995, Jaffe 1986, Audretsch & Feldman 1996) has shown that patents are a likely outcome of overall R&D investments, such that one must expect a positive correlation between past R&D investments and patent stocks. Moreover, patent stocks are a direct control for serial correlation in the dependent variable, avoiding spurious correlation to occur among the set of policy variables with the dependent variable. Appendix B describes of our metrics on renewable and fossil-fuel patents.

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 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 average of the scores for emission limits of NOx, SO_x and PM.For both type of instruments, we then generate normalized indexes which vary from 0 to 1, with 1 indicating the highest level of stringency in that given instrument observed over the sample period.[6]

Figures 1 and Figure 2 display the dynamics of the key variables at stake. The first and second rows of Figure 1 show the evolution of the production of renewable energy and fossil-based patents for selected OECD and developing countries[7], while the third row shows the ratio of the green to brown patents rk. Over the sample period, we observe a global upward trend in patenting in both renewable and fossil fuel technologies, but the latter grew at a significantly slower pace

[6]We do this in order to facilitate the comparison of the parameter estimates for the two policy instruments. Importantly, this transformation does not affect the covariance of either the dependent variable or the set of control variables with the two policy variables.

[7]These countries are Russia, India, Indonesia, China and South Africa.

than the former. All countries in the sample show a re-direction of innovation towards renewable technologies. This phenomenon is more pronounced in non-OECD countries, although in OECD countries, the level of patenting activity is higher. Figure 2 shows the evolution of the threshold variable over time (rK, in the first row), the dynamics of CC (second row) and MB policies (third row). We observe that command-and-control policies are vastly adopted in developed countries, while their score is lower and displays less variation in developing countries. 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.

[Figure 1 about here.]

[Figure 2 about here.]

Lastly, we include the following control variables: (i) electricity production ($\ln EP$ in kW per hour, in logs); (ii) electricity consumption ($\ln EC$ in kW per capita, in logs); (iii) electricity import share in domestic production (EM); (iv) electricity export share in domestic production (EX); (v) GDP ($\ln GDP$ measured in thousands of 2011 USD PPP, in logs); (vi): population ($\ln POP$, in logs); (vii) human capital index (HC). Control variables (i)-(iv) are obtained from the World Development Indicators Database (WDI 2020) and capture important features related to the energy system of a given economy. Economic variables (v) and (vi) are typical controls for the size of a given economy and its living standards and taken from the Penn World Tables, version 10.01 (Feenstra et al. 2015). Their joint introduction grasp the overall distance of a country to the economic frontier. The human capital index combines information on the average years of schooling from Barro & Lee (2013) with rates of return of education as estimated by Psacharopoulos (1994). The motivation for introducing human capital (*vii*) is to measure preferences for renewable energy, which, we hypothesize, increases with human capital (Kim et al. 2018).

[Table 1 about here.]

Table 1 reports the summary statistics of our balanced sample, which includes 759 observations from 33 countries over the years 1990-2012.

4.2 Model specification

Estimating and comparing Models (2) to (4)-(5) requires addressing several important empirical challenges which complicate the identification of the policy effects: accounting for both unobserved heterogeneity in the context of slowly changing policy variables and for the endogeneity of the policy variables; implementing an algorithm searching for thresholds in policy effectiveness; developing a model selection procedure to compare the performance of the different models. Here we briefly describe how we address these challenges. Appendix C provides a more detailed discussion.

Unobserved heterogeneity and policy endogeneity.[8] To address unobserved heterogeneity and endogeneity, we follow two complementary strategies. First, we control for unobserved heterogeneity using the pre-sample mean of the dependent variable rather the relying on within-country variations. This approach is better suited to deal with slow moving explanatory variables such as climate

[8]See Subsections C.1 and C.2 of Appendix C for a thorough presentation.

policies (Blundell et al. 2002). Second, we address endogeneity concerns via a shift-share instrumental variable (IV) approach which controls for reverse causality and omitted variable bias. For each country, our IV is built using information on environmental policies implemented by a subset of similar countries. Similarity here is defined according to the sharing of common legal origins, and is thus predetermined by construction (LaPorta et al. 1999). The exclusion restriction is that the same legal origins are correlated with the general capacity to innovate, which is included as control in our regression, rather than with the direction of innovative activities. As suggested by (Wooldridge 2015), we implement this instrument using a control function approach that is better suited to deal with non-linearities and interaction terms. Overall, while the level of data aggregation does not allow to fully resolve endogeneity issues in our context, our approach combining control function and threshold models shows how to jointly tackle challenging estimation issues.

Searching for threshold values of relative specialization.[9] To search for thresholds effects, we rely on the estimation and inference methodology developed by Hansen (1999) to determine the number of concealed thresholds as well as their values. This method introduces econometric techniques appropriate for the detection of threshold value(s) of a given variable that condition the effect of another variable. The key idea is that, rather than arbitrary imposing a threshold value γ (Model 4) of specialization rK below and above which policy effectiveness varies, the algorithm lets the threshold vary incrementally – percentile by percentile – with rK, tests for non-linearities in policy effectiveness for every percentiles of

[9]Further details on the estimation of thresholds and inference thereof are presented in Appendix C.3.

rK, and chooses threshold γ which minimises the sum of squared errors.

Clearly, this algorithm is attractive in that it imposes no prior on the location of the threshold γ over the distribution of rK. Given the existence of one threshold, the program searches for a second threshold iteratively using the first threshold as given. Conditional on the existence of a first and a second threshold, the same procedure is extended to determine whether additional thresholds exist. Relative to the seminal contribution of Hansen (1999), we amend the model in one important aspect. In his application on firm financial constraints, Hansen (1999) interacts the threshold variable (long term debts) with one variable of interest (cash flow). In our case, we interact the threshold variable, namely the ratio of knowledge stocks rK, with the two policy variables of interest, namely market-based (MB) and command-and-control (CC) policies.

Choice of best fit.[10] Our objective is to choose the one specification which most accurately reflects the underlying data generating process. Model (3) is nested into Model (2), but threshold Models (4) and (5) do not represent unconstrained versions of Models (2) nor (3). Because all specifications share some common explanatory variables, we consider them as overlapping models. This excludes the possibility of using the log-likelihood ratio test for nested models or Vuong's statistics for strictly non-nested models (Vuong 1989). Our strategy to determine the best fit is to provide three sets of indicators suited for model selection in the case of overlapping models: (i) the adjusted R-squared[11]; (ii) indicators based on the Akaike information criterion (AIC), with a correction for small samples

[10] See Appendix C.4 for a detailed presentation of the procedure.

[11] Its most appealing feature is that its relationship with the number of explanatory variables can either increase or decrease, depending on whether the additional regressor(s) brings valuable information to the model

(AIC_c)[12]; (*iii*) Vuong's $2LR$ statistics for overlapping models (Vuong 1989).[13]

5 Econometric Results

5.1 Results

Prerequisite for identification. The key identifying assumption is that the policy effort of countries with similar legal origins is uncorrelated with the direction of technological change, conditional on the set of controls that absorb – among other things – global knowledge spillovers (time fixed effects), the general innovation capacity (knowledge stock $\ln K_{-(f+g),t-1}$) and different initial level in the direction of technical change (pre-sample mean of the dependent variable). Although this assumption is not testable *per se*, a clear indication of violation would be that legal origins exhibits specific rates of innovation before the period of analysis. We address this concern by comparing the compound annual growth rate of $\ln rK_{g/f,t}$ between 1985 and 1990 between groups of countries with different legal origins by means of a T-test an F-test (see Table 2). This test does not reject the null hypothesis that there are no pre-existing differences in the direction of innovation across countries with different legal origins.

[Table 2 about here.]

Moreover, the control function approach allows for a simple test of policy en-

[12]Following Burnham & Anderson (2004), we use transformed values of AIC and AIC_c, respectively $\exp(-\frac{\triangle}{2})$ and ω, as both can be interpreted as weights of evidence in favor of one model *vis-à-vis* the others

[13]The latter is a two-by-two model comparison based on the usual log's ratio statistics $2LR$, where the models compared refer to overlapping specifications displayed in Equations (2), (3) and threshold specifications (4), (5) or any higher number of threshold deemed relevant.

dogeneity by assessing the statistical significance of the first-stage residuals in the second-stage regression (Wooldridge 2015). The results are reported in the last row of Table 3. We find that the policy vector $\mathbf{P}$ is endogenous across the various specifications, corroborating the use of the control function approach.[14]

Main results. Table 3 reports the results of the three models discussed in Section 3. We first discuss the significance of the estimates, while we present a comprehensive simulation aiming to quantify the policy effects in Subsection 5.2.

Column 1 shows the results of a parsimonious specification of the linear specification (Eq.2), which we label Linear $1P$. This includes one environmental policy index (ALL), which includes both MB and CC instruments as a homogeneous block. First, ALL does not contribute to explain the direction of innovation towards the more radical technology. Second, in line with Aghion et al. (2016) and Noailly & Smeets (2015), the coefficient for $\ln rK_{g/f}$ is positive and statistically significant at the 1% level. This confirms path dependency in the direction of energy innovation: countries with more experience in renewable relative to fossil fuel innovation have a comparative advantage in further specialization. While testifying to the existence of a first-mover advantage for early innovators in the realm of energy, this result also implies that laggard countries can be locked in a fossil fuel technological paradigm. Third, we find no evidence that cross-fertilization plays a role in steering innovation: the coefficients associated with $\ln K_f$ and $\ln K_{-(f+g)}$ (i.e., the fossil fuel and overall knowledge stocks, respectively) are not significant.

Column 2 (Linear $2P$) allows for the effect of MB and CC instruments to vary and shows that the direction of innovation is affected differently by policy

[14]The F-statistics of the first-stage regression reported at the bottom of Table D1 highlights the strength of our vector of instruments.

instruments of different nature. The coefficient of CC policies is both positive and significant, while the one associated with MB policies is not. The aggregate policy index in Column 1 masks heterogeneous impacts depending on the policy types. This further motivates our focus on the distinct effects of CC and MB policies.

[Table 3 about here.]

Column 3 shows the results of estimating Model (3), where we interact $\ln K_{g/f}$ with the two policy variables. Two key results emerge. First, the coefficients of the interaction terms indicate that MB policies are effective in redirecting innovation towards renewable energy technologies only when the relative stock of competencies in these technologies is large *enough*. Observing that $\partial \ln rK_{g/f}/\partial MB = -1.408 + .837 \times \ln rK_{g/f}$, we find that the effect of MB policies is negative for the first two-thirds of $\ln K_{g/f}$, while it turns positive for the remaining 34 percentiles.[15] Second, we find no evidence that the policy effectiveness of CC changes linearly with specialization variable $\ln rK_{g/f}$.

Column 4 presents the results of the two-threshold specification (Model 5).[16] The two-threshold specification reveals the existence of three regimes. In the first regime, where $\ln rK_{g/f}$ is low (below the 47^{th} percentile), only CC policies affect the direction of innovation towards renewables. The coefficient of MB is not statistically different from zero, but its sign is consistent with the results of Column 3 (interaction model). Hence, in this first regime, countries which implement CC policies successfully steer innovation towards the novel technology

[15] More precisely, this effect is significantly negative below the 32^{th} percentile of $\ln rK_{g/f}$, and significantly positive above the 92^{th} percentile.

[16] The point estimates of the two thresholds are 1.292 and 2.198, which correspond to respectively the 47^{th} and the 89^{th} percentiles of the distribution of the threshold variable ($\ln rK_{g/f}$). See Subsection D.2 of Appendix D.

and away from the incumbent one; this is not the case for countries which rely on MB policy instruments. The second regime, which is characterized by values of $\ln rK_{g/f}$ between the 47^{th} and the 89^{th} percentile, gives similar results, although the negative effect of MB policies disappears entirely. CC policies remain positive and significant. Lastly, in the third regime, we observe a switch in the relative effectiveness of the MB and CC policy instruments: the former become effective, the latter ineffective. That is, a country that has accumulated a considerable amount of experience in renewable as opposed to fossil fuel innovation (i.e., the top 11% of the country-year observations in our sample) can rely exclusively on market-based policies to ensure that innovation keeps away from the incumbent technology and is directed towards the new technological paradigm.

Model selection. Table (4) provides information on the goodness of fit of the various models. We compare the models sequentially: Column 1 (Linear 1P model) and Column 2 (Linear 2P model); Column 2 and Column 3 (Interaction model); Column 3 and Column 4 (Threshold model).

First, we observe a higher adjusted R-squared and LL value for the Linear $2P$ model as compared to the Linear $1P$ model. Vuong's $2LR$ statistics is negative and significant (at 10% level), indicating that the Linear $2P$ model outperforms the Linear $1P$ one. In a similar fashion, both the AIC and the AIC_c scores exhibit lower values for the Linear $2P$ model. These results suggest that the the distinction between MB and CC policies is statistically relevant – and economically meaningful – since it yields a significant increase in the explanatory power of the model.

Second, we test whether the linear $2P$ model - which assumes a constant policy effect - is outperformed by the interaction - which implies that the effectiveness of policy is linearly dependent on the value of the specialization variable $\ln rK_{g/f}$. Indeed, Vuong's $2LR$ statistics is large, negative, and statistically highly significant. Furthermore, the increase in the adjusted R-squared and reduction in the LL, AIC, and AIC_c values are sizable. Thus, there is overwhelming evidence that policy effectiveness differs depending on the country's relative level of competencies.

Third, we observe a higher adjusted R-squared, and lower values for the LL, AIC and AIC_c for the threshold model as opposed to the interaction model. Vuong's $2LR$ statistics is negative and significant, pointing to the dominance of the threshold specification. This implies that, if policy effectiveness depends on relative competencies, it does so in a non-linear fashion. Since pairwise comparisons are transitive, we conclude on the global dominance of the threshold specification *vis-à-vis* all others. This is further confirmed by the two Akaike-based statistics, which provide strong evidence of evidence in favor of the global dominance of one model over all others, independently of whether we use AIC or AIC_c, both statistics $\exp(-\frac{\triangle}{2})$ or ω.

[Table 4 about here.]

Two important conclusions can be drawn from this exercise. First, the distinction between MB and CC policy matters when it comes to estimating their impacts on energy innovation. Second, there are regimes across which policy effectiveness differs significantly and within which policy effectiveness is stable.

Decomposing policy effects on renewable and fossil-fuel innovation. Given the nature of the dependent variable – defined as the ratio of renewable over fossil fuel innovation – it is key to understand how MB and CC affect the numerator and/or the denominator, respectively. To this end, we run separate regressions on the numerator and denominator of our dependent variable with the same set of explanatory variables as in model 4. This allows us to distinguish where the net policy effect stems from.[17] In our so doing, we take the estimated threshold as given and interact the MB and CC variables with dummy variables representing each of the three regimes.

Table 5 displays the two models which explore separately the effect of the policy instruments on the level of innovation in renewable (Model 5) and fossil-efficient energy technologies (Model 6), alongside Model 4 from Table 3. The mechanisms at play in the three regimes are different. In the first regime, CC policies promote innovation in renewables, while MB policies promote innovation in fossil-efficient technologies. In this first regime characterized by comparatively higher competencies in fossil-fuel innovation, CC policies, send a clear signal to private actors on the future of fossil fuels within a country and deter brown innovation, while MB policies are not successful. In the second regime, CC policies redirect innovation towards green technologies exclusively. Conversely, MB policies start to have a beneficial impact on innovation, but promote innovation in both fields. In the third regime, MB policies provide actors with the necessary incentives to undertake invention activities in carbon-free energy solutions. Differently from the previous two regimes, CC policies do not display any inducement effect.

[Table 5 about here.]

[17] Because $\ln rk_{g/f} = \ln k_g - \ln k_f$, the reported parameter estimates pertaining to the dependent variable $\ln rk_{g/f}$ all sum to the estimate pertaining to $\ln k_g$ and $\ln k_f$ such that $\hat{\beta}_{rk_{g/f}} = \hat{\beta}_{rk_g} - \hat{\beta}_{rk_f}$.

Altogether, we conclude that three *appropriate* policy regimes exist. They are defined as follows: $\mathbf{P}^{\star}_{R1} = \{CC\}$; $\mathbf{P}^{\star}_{R2} = \{CC; MB\}$; $\mathbf{P}^{\star}_{R3} = \{MB\}$. A policy is deemed *effective* when the policy is activated under the *appropriate* policy regime.

5.2 Quantification

We quantify the effectiveness of policy regimes $\mathbf{P}^{\star}_{R1}$, $\mathbf{P}^{\star}_{R2}$ and $\mathbf{P}^{\star}_{R3}$ in redirecting technical change towards renewable energy by simulating counterfactual policy scenarios in which countries implement what we qualify as *optimal* policy choices, conditional on regime in which the country-year observation belongs. We simulate two scenarios: the optimal policy scenario at the observed level of stringency ($\mathbf{P}^{\star}_{\mathbf{obs}}$) and the optimal policy scenario at the highest level of stringency ($\mathbf{P}^{\star}$). We compare these scenarios to the observed policy as implemented by each country ($\mathbf{P}_{\mathbf{obs}}$). [18]

Figure 3 provides the dynamics of the simulated variable of interest (the relative specialization as proxied by the ratio of renewable to fossil fuel patent stock $\mathbf{r\tilde{K}_{g/f}}$) up to year 2012 for six countries.[19] A broad, but important, preliminary remark is that the simulation results are consistent with what one should expect. The performance of the observed policy vector $\mathbf{P}_{\mathbf{obs}}$ ranks below that of appropriate policy vectors where stringency is set at the countries' observed value ($\mathbf{P}^{\star}_{\mathbf{obs}}$), which itself ranks below the performance of of such appropriate policies implemented at their highest stringency ($\mathbf{P}^{\star}$). On the whole, the economic effect of policies in directing technical change is quite substantial in all displayed countries.

[18] Appendix E provides the details of the simulation exercise.

[19] These countries are: China, Germany, France, Mexico, The Netherlands, and The USA. They represent archetypal examples of simulated energy transitions over the three policy scenarios. Figure E1 provides the simulation results for all countries in our sample.

[Figure 3 about here.]

In the first row, we display results for Mexico and China, two countries which are characterized by a very low initial level of green specialization, combined with a low initial level of innovation output. Although the two countries display similar observed dynamics of ($r\tilde{K}^{\mathbf{P_{obs}}}_{g/f}$, the black line), the simulations under different policy scenarios $\mathbf{P^{\star}_{obs}}$ and $\mathbf{P}^{\star}$ yield different dynamics of their specialization $r\tilde{K}$ and offer grounds for further interpretation.

Take Mexico. The fact that the black line depicting the outcome of observed policies $\mathbf{P_{obs}}$ and appropriate policies set at the country's maximum values ($\mathbf{P^{\star}_{obs}}$) display the same dynamics indicates that it is neither the choice nor the timing of policies which prevented Mexico from increasing its relative specialization in renewable technologies. Rather, it was the stringency of implemented policies which proved too low to redirect innovation towards renewables. Instead, the gap between the appropriate policies at the country's maximum values ($\mathbf{P^{\star}_{obs}}$) and the appropriate policies at their highest possible intensity ($\mathbf{P}^{\star}$) is evidence of the inability of the country to break out from fossil fuel innovation comes from its lack of commitment – a synonym for stringency of the chosen policies.

Differently from Mexico, China is characterized by inadequate policy timing as well as inadequate policy intensity: both limit its ability to direct innovation towards renewable technologies. In fact, the scenario with observed values represents an intermediate case that outperforms the scenario with observed policies (hence there is an inadequate policy timing) and is outperformed by the scenario with policies at the maximum (hence there is an inadequate policy intensity). Interestingly, the policy diagnosis which characterizes China applies to a large panel of countries in the sample, including countries with higher initial level of specialization, and stronger initial innovation capabilities.[20]

In many countries, the dynamics of $rK_{g/f}$ stemming from observed policies $\mathbf{P}^{\star}_{\mathbf{obs}}$ locates somewhat far from the dynamics stemming from appropriate policies $\mathbf{P}^{\star}$. This is the case, for instance, for Germany and the Netherlands, but with different policy implications. In the case of Germany, we observe policies choices (black line) that conforms to appropriate policies (red line), although with a delay. Starting from 2004 onwards, the shape and slope of the black curve perfectly mimic that of the red curve, indicating the set of implemented policies conform to appropriate policies.The simulated dynamics for the Netherlands, although similar, offers a slightly different interpretation. Up until 2006, the simulated dynamics of $rK_{g/f}$ stemming from observed policies $\mathbf{P_{obs}}$ is clearly negative, thereby displaying an increase in specialization in fossil-based innovation. This is consistent with IEA (2020), which comments that the country remains heavily reliant on fossil fuels, although notable progress towards carbon-neutral economy are noteworthy.Once observed policies conform to appropriate policies, the country swiftly moves towards the third regime.

In the last row, we show two countries with yet different dynamics. Both France and the US provide policies in support of innovation but fail to direct innovation towards renewable technologies. In France, $\mathbf{P}^{\star}_{\mathbf{obs}}$ could suffice in reaching the third regime. Therefore, the problem does not lie in its policy stringency, rather in its timing. In fact, implemented policies $\mathbf{P_{obs}}$ drag the innovation further away from the second regime and towards the first. Altogether, France displays a poor policy choice. This is consistent with the fact that France has chosen to make nuclear

[20]See Figure E1 in Appendix E.

energy its main energy source[21] downplaying the development of renewable energy sources as a key policy objective.

The USA is a clear example where the observed policy stringency performs exceptionally well in the first and second regime (command-and-control policy), and exceptionally poorly in the third innovation regime (market-based policies) given the country's level of relative specialization. In fact, the observed values in $rK_{g/f}$ displayed under $\mathbf{P}^{\star}_{\mathbf{obs}}$ (MB policies in the third regime) are so low that it prevents the country from remaining in the third regime, as implied by cyclical pattern of the gray line. Once in the third regime, the stringency MB policies is so poor that the high level of specialization $rK_{g/f}$ cannot be sustained, and declines.

6 Conclusion

We have examined how policy choice - i.e., the combination of market-based and command-and-control policy instruments - affects the direction of innovation towards renewable and away from fossil-fuel energy technologies. We conclude that, depending on the level of a country's relative capabilities, there exists three *effective* policy regimes to break out from focusing primarily on fossil-fuel-based innovation: a first regime in which command-and-control policies alone are implemented; a second regime in which market-based policies are added to the policy portfolio; a third regime in which command-and-control policies are phased out.

Our simulations also yield three broader conclusions. First, the time needed to reach the last innovation regime may be relatively swift. When policies are implemented in the appropriate regimes, a given country may reach the last innovation

[21] Although the country performs poorly in renewable energy innovation relative to fossil fuel innovation, it also performs extremely well in terms of per capita gas emission.

regime within a decade. Instead, countries which do not activate the *appropriate* policy given their level of specialization may never succeed in directing technical change. Second, accumulated competences in the new technology matter. It takes longer for countries lagging behind in their specialization in renewable energy, relative to efficient fossil-fuel energy, to reach the third regime. This underlines the necessity for all countries to provide direct public support for R&D investments to build their competence base. Third, in directing technical change, the policy effects are always bounded in time. The systematic concavity of our simulation implies that the marginal effect of appropriate policies, initially substantial, depreciate overtimes. Once in a regime, policy effectiveness has exhausted the possibilities offered by the new policy in directing technical change.

Policymakers should address three key aspects when designing policies. First, they must carefully compose policy portfolios, which include diverse instruments whose rationales, mechanisms and expected effects come with a great deal of heterogeneity. Second, policy stringency is crucial; without sufficient commitment, even well-designed portfolios may fail. Finally, timing is critical, as the same policy composition and stringency may yield opposite effects depending on the context. For instance, market-based policies, which always steer innovation towards the technology in which the country is specialized, may eventually misdirect efforts if implemented too early or in isolation.

Altogether, our main result is crystal clear. The set of policies implemented are paramount in directing innovation towards novel technologies. Choosing the appropriate policy at the appropriate time, and correctly timing the sequencing of policy instruments, can yield a swift transition towards a greener economy.

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Figure 1: Evolution of renewable patent counts k_g, of fossil fuel patents counts Pkf, and of the ratio of the two patent counts (rk) for selected OECD and non-OECD countries

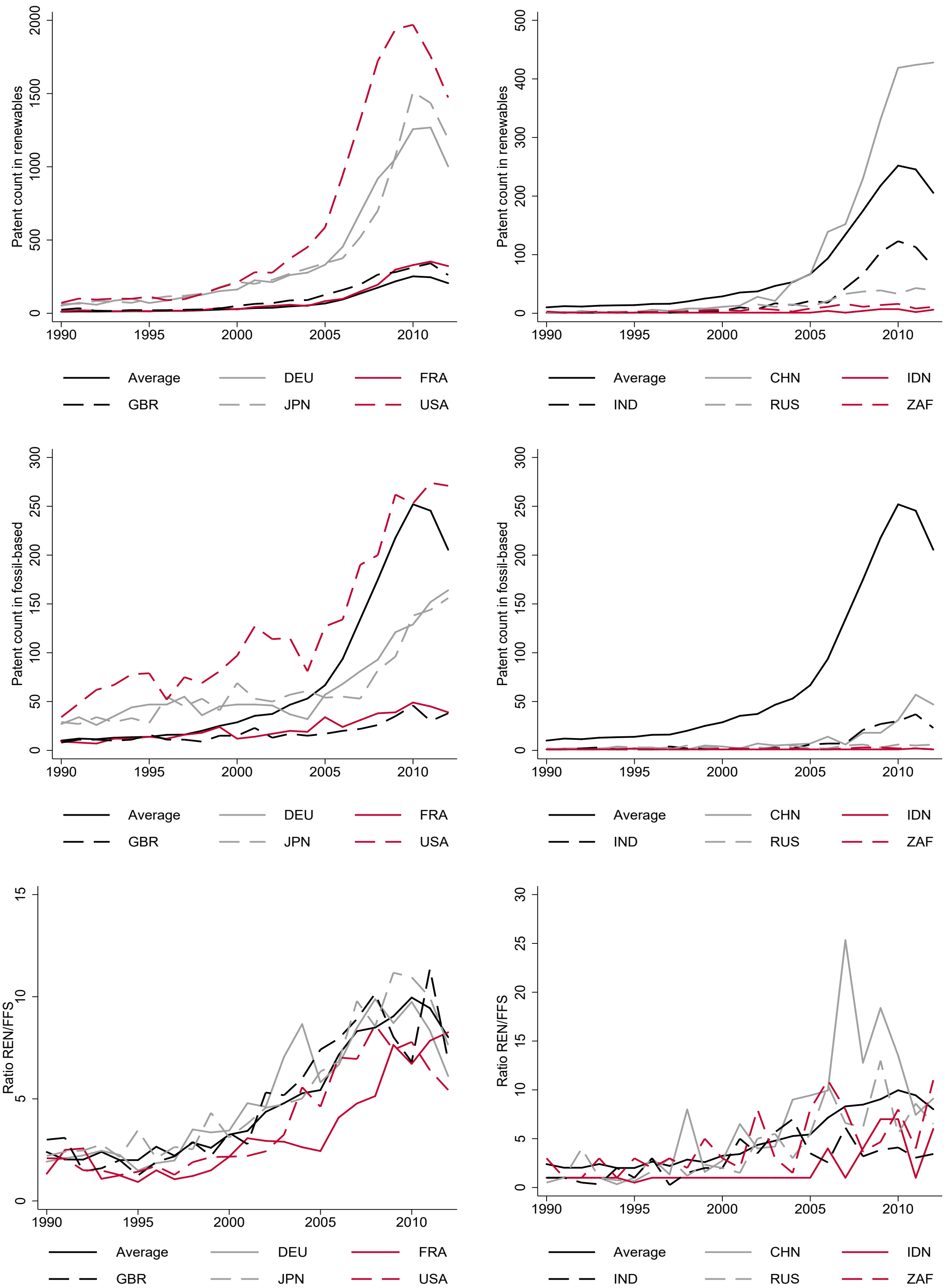


Figure 2: Evolution of the threshold variable rK and of MB and CC policy scores for selected OECD and non-OECD countries

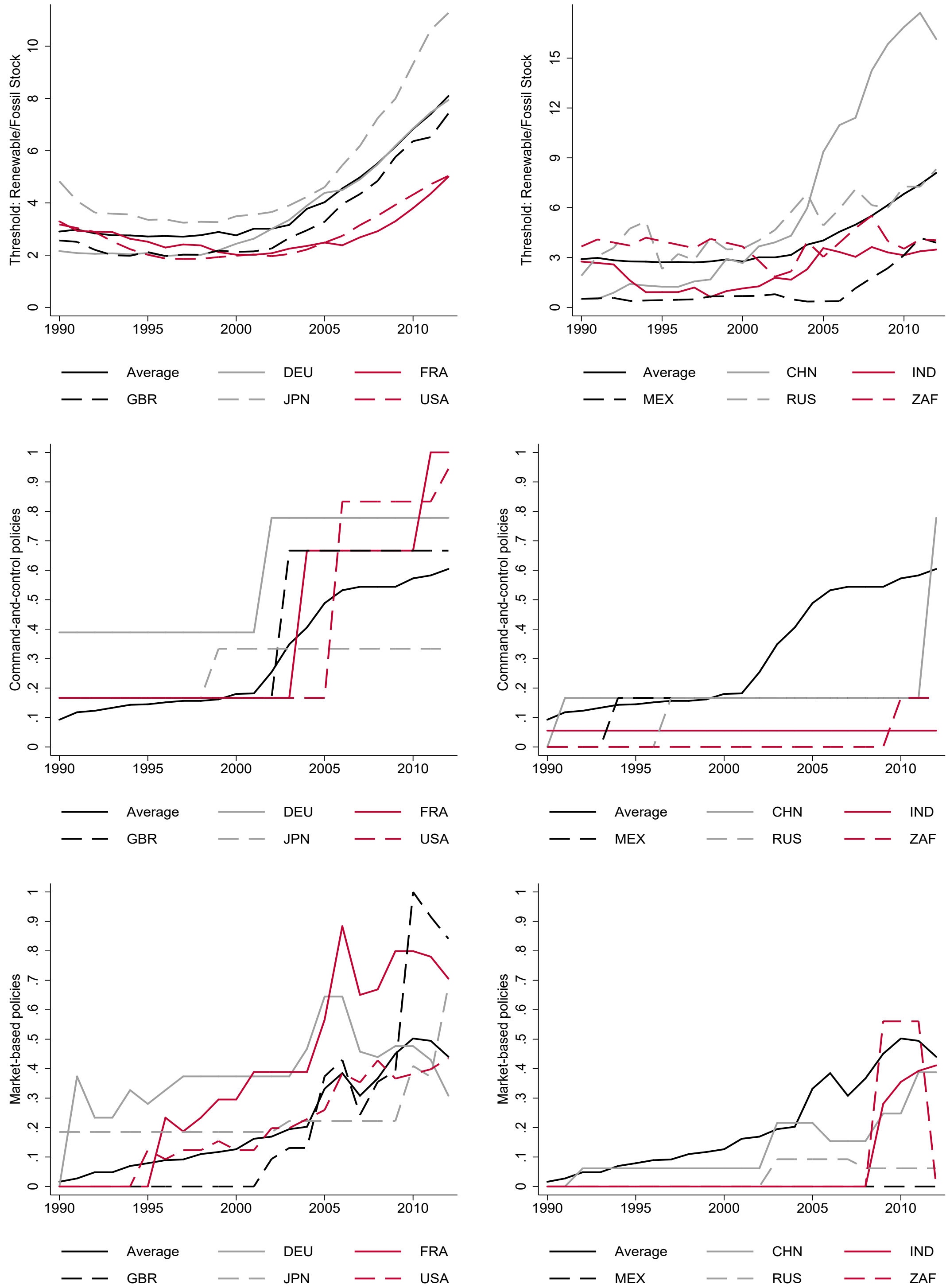
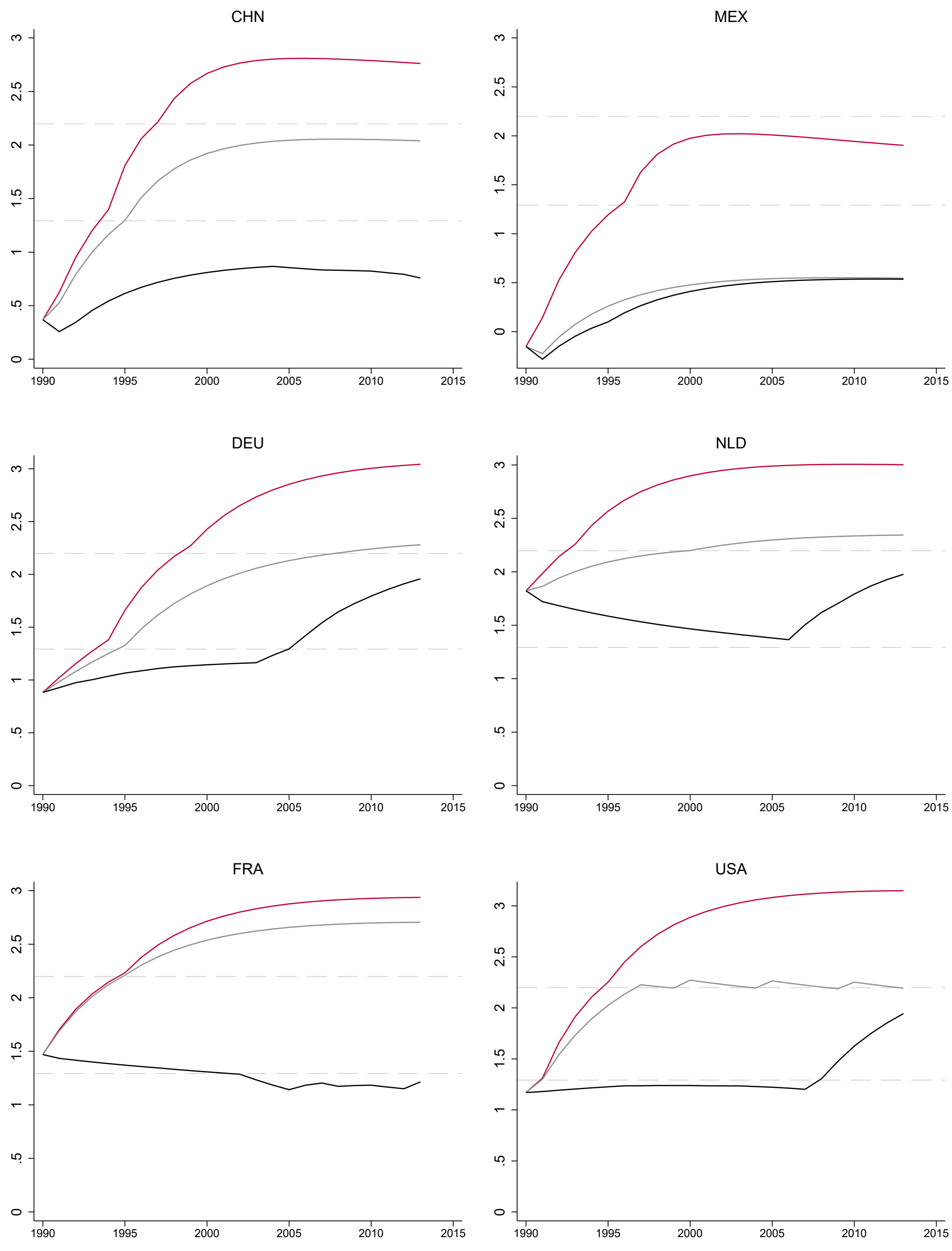


Figure 3: Simulating the dynamics of the renewable to fossil-fuel patent stock $\ln rK$ under alternative policy scenarios.



Specialization variable $\ln r\tilde{K}_{g/f}$ displayed, using alternatively $\mathbf{P_{obs}}$ (black line), $\mathbf{P^{\star}_{obs}}$ (grey line), and $\mathbf{P}^{\star}$ (red line) for Equation E1. The dashed horizontal grey lines denote the first ($\hat{\gamma}_1$) and second ($\hat{\gamma}_2$) thresholds.

Table 1: Summary statistics ($N = 759$)

Variable	Name	Mean	Median	SD	Min	Max
Renewable/Fossil patent flow (log)	$\ln rk_{g/f}$	1.164	1.099	0.915	-2.398	3.653
Renewable patents	k_g	74.769	10.000	217.178	0.000	1969
Fossil patents	k_f	12.470	2.000	30.199	0.000	273
Pre-Sample Mean (log)	PSM	0.834	0.854	0.590	0.000	1.948
Renewable/Fossil fuel patent stock (log)	$\ln rK_{g/f,t-1}$	1.332	1.337	0.744	-0.693	3.160
Fossil fuel stocks (log)	$\ln K_{f,t-1}$	2.630	2.506	1.801	0.000	7.298
Total Knowledge Stock (log)	$\ln K_{-(g+f),t-1}$	8.736	8.849	2.198	2.370	13.435
Market-based policies	MB	0.211	0.131	0.234	0.000	1.000
Command-and-Control policies	CC	0.311	0.167	0.276	0.000	1.000
Electricity production (Kw per hour, log)	$\ln P_{Kw/h}$	13.435	13.309	1.318	10.845	16.881
Electricity Consumption (Kw per capita, log)	$\ln C_{Kw/pc}$	2.156	2.403	1.506	-.959	5.221
Electricity Imports[a] (Imported Kw)	M_{Kw}/P_{Kw}	0.075	0.039	0.096	0.000	0.585
Electricity Exports[a] (Exported Kw)	X_{Kw}/P_{Kw}	0.067	0.031	0.100	0.000	0.573
Gross Domestic Product (log)	$\ln GDP$	6.374	6.215	1.246	3.285	9.653
Population (log)	$\ln pop$	3.370	3.434	1.564	0.687	7.212
Human Capital	HC	2.978	3.114	0.522	1.487	3.719

[a] Electricity Imports and Exports is their share in electricity production.

Table 2: Results of Common Trends Hypothesis

H_0	H_1	Test	Statistics	P-value
$\mu_{UK} = \mu_{-UK}$	$\mu_{UK} \neq \mu_{-UK}$	T-test	0.892	.379
$\mu_{FR} = \mu_{-FR}$	$\mu_{FR} \neq \mu_{-FR}$	T-test	0.390	.700
$\mu_{EE} = \mu_{EE}$	$\mu_{EE} \neq \mu_{-EE}$	T-test	2.656	.012
$\mu_{GE} = \mu_{-GE}$	$\mu_{GE} \neq \mu_{-GE}$	T-test	0.347	.731
$\mu_{SC} = \mu_{-SC}$	$\mu_{SC} \neq \mu_{-SC}$	T-test	0.987	.331
All growth rates are equal	At least one growth rate differs	F-test	1.740	.169

The variable of interest is the compound annual growth rates of the ratio of knowledge stocks in renewable energy over the knowledge stocks in fossil fuels $\ln rK_{g/f,t}$ between 1985 and 1990. UK refers to countries abiding by the legal origins of United Kingdom. FR refers to countries abiding by the legal origins of France. EE refers to countries abiding by the legal origins of Eastern Europe. GE refers to countries abiding by the legal origins of Germany. SC refers to countries abiding by the legal origins of Scandinavia.

Table 3: Parameter estimates for the policy-induced model of green innovation

	Linear $1P$	Linear $2P$	Interaction	Threshold
	(1)	(2)	(3)	(4)
$\ln rK_{g/f,t-1}$	0.400***	0.411***	0.225**	0.258**
	(0.122)	(0.116)	(0.114)	(0.108)
$\ln K_{f,t-1}$	0.003	-0.046	-0.061	-0.080
	(0.164)	(0.120)	(0.118)	(0.125)
$\ln K_{-(f+g),t-1}$	0.144	0.139	0.172*	0.176*
	(0.111)	(0.095)	(0.092)	(0.095)
ALL policies	0.158			
	(1.999)			
MB policies		0.129	-1.408*	
		(0.391)	(0.735)	
$MB \times \ln rK_{g/f,t-1}$			0.837*	
			(0.492)	
CC policies		1.161**	0.816	
		(0.510)	(0.645)	
$CC \times \ln rK_{g/f,t-1}$			0.202	
			(0.353)	
$MB \times \mathbb{1}(\ln rK_{g/f,t-1} \leq \hat{\gamma}_1^r)$				-0.692
				(0.576)
$MB \times \mathbb{1}(\hat{\gamma}_1^r < \ln rK_{g/f,t-1} \leq \hat{\gamma}_2)$				-0.021
				(0.506)
$MB \times \mathbb{1}(\ln rK_{g/f,t-1} > \hat{\gamma}_2)$				1.680*
				(0.947)
$CC \times \mathbb{1}(\ln rK_{g/f,t-1} \leq \hat{\gamma}_1^r)$				1.130**
				(0.499)
$CC \times \mathbb{1}(\hat{\gamma}_1^r < \ln rK_{g/f,t-1} \leq \hat{\gamma}_2)$				1.371**
				(0.628)
$CC \times \mathbb{1}(\ln rK_{g/f,t-1} > \hat{\gamma}_2)$				0.609
				(0.789)
F-Stat H_0: Exogeneity of $\mathbf{P}$	2.75*	3.70	9.71**	11.09*

Dependent Variable: (Log of the) Ratio of renewable to fossil fuel patents ($\ln rk_{g/f,it}$). $N = 759$. Bootstrapped standard errors in parentheses produced from 1,000 block-bootstrapped samples. *** p<0.01, ** p<0.05, * p<0.1. See Appendix C for details about the estimation methods. Values (percentiles) of the two thresholds are $\hat{\gamma}_1^r = 1.292$ (47^{th} percentile) and $\hat{\gamma}_2 = 2.198$ (89^{th} percentile) (see Table D2). All regressions include a full vector of unreported year fixed effects, a dummy variable for observations with no fossil fuel patent production ($k_{f,t} = 0$). The set of unreported control variables is: $\ln EP$: Electricity production (in kW, in logs); $\ln EC$: Electricity consumption per capita (in kW per hour, in logs); EM: electricity import share in domestic production; EX: electricity export share in domestic production; HC: Human capital index;$\ln GDP$: GDP (in thousands of 2011 USD PPP, in logs);$\ln POP$: Population (in logs). Regressions also include unreported control function errors from a first IV stage on policy variable MB and CC.

Table 4: Model comparison between the linear, interaction and threshold specifications. Assessing goodness of fit measures

	Linear $1P$	Linear $2P$	Interaction	Threshold
R-squared	0.647	0.655	0.670	0.676
Adjusted R-squared	0.629	0.637	0.651	0.655
LL	-613.8	-605.2	-587.7	-580.9
Vuong's $2LR$		-17.217	-34.907	-13.535
$\Pr(\mathbf{F} \succeq \mathbf{G})$		0.091	0.000	0.041
$\Pr(\mathbf{F} \prec \mathbf{G})$		0.909	1.000	0.959
AIC	1301.6	1288.4	1261.4	1255.9
Akaike $\exp(-\frac{\triangle}{2})$	0.000	0.000	0.063	1.000
Akaike ω	0.000	0.000	0.059	0.941
AIC_c	1305.5	1292.7	1266.7	1262.3
Akaike $\exp(-\frac{\triangle_c}{2})$	0.000	0.000	0.106	1.000
Akaike ω_c	0.000	0.000	0.096	0.904

Dependent Variable: (Log of the) Ratio of renewable to fossil fuel patents ($\ln rk_{g/f,it}$). $N = 759$. Linear $1P$ refers the case where the policy vector reduces to a scalar (only one policy including both MB and CC policies) using Equation (2. Linear $2P$ uses to Equation (2) where the policy vector distinguishes MB and CC policies. Vuong's ratio $2LR$ statistics for partially overlapping models compares the current specification ($\mathbf{G}$) with the specification of the previous column ($\mathbf{F}$) as in the case of the LR test: Vuong's ratio $2LR = LL_{\mathbf{F}} - LL_{\mathbf{G}}$. A positive value indicates that specification $\mathbf{F}$ is to be preferred over specification $\mathbf{G}$: $\mathbf{F} \succeq \mathbf{G}$. A negative value indicates that specification $\mathbf{G}$ is to be preferred over specification $\mathbf{F}$: $\mathbf{F} \prec \mathbf{G}$. The last two rows provide critical probability values for Vuong's $2LR$ produced from 1,000 blocked bootstrapped samples.

Table 5: Threshold regressions using as the dependent variable the log of ratio of renewable over fossil fuel patents ($rk_{g/f,t}$), the number of renewable patents (k_g) and the number of fossil fuel patents (K_f), respectively

	(4)	(5)	(6)	(7)	(8)
	$\ln rk_{g/f}$	$\ln k_g$	$\ln k_f$	$\ln k_g$	$\ln k_f$
$\ln rK_{g/f,t-1}$	0.258**	0.522***	0.265***		
	(0.108)	(0.099)	(0.103)		
$\ln K_{g,t-1}$				0.546***	0.174
				(0.099)	(0.113)
$\ln K_{f,t-1}$	-0.080	0.645***	0.725***	0.183*	0.461***
	(0.125)	(0.120)	(0.111)	(0.100)	(0.083)
$\ln K_{-(g+f),t-1}$	0.176*	0.051	-0.125	0.001	-0.108
	(0.095)	(0.097)	(0.079)	(0.094)	(0.088)
$MB \times \mathbb{1}(\ln rK_{g/f,t-1} \leq \hat{\gamma}_1^r)$	-0.692	0.891	1.584***	0.679	0.888
	(0.576)	(0.554)	(0.563)	(0.591)	(0.640)
$MB \times \mathbb{1}(\hat{\gamma}_1^r < \ln rK_{g/f,t-1} \leq \hat{\gamma}_2)$	-0.021	0.706*	0.727*	0.644*	0.723
	(0.506)	(0.386)	(0.439)	(0.387)	(0.441)
$MB \times \mathbb{1}(\ln rK_{g/f,t-1} > \hat{\gamma}_2)$	1.680*	2.217***	0.538	1.829***	1.015
	(0.947)	(0.733)	(0.882)	(0.708)	(0.931)
$CC \times \mathbb{1}(\ln rK_{g/f,t-1} \leq \hat{\gamma}_1^r)$	1.130**	0.918**	-0.211	0.874**	0.292
	(0.499)	(0.376)	(0.506)	(0.388)	(0.443)
$CC \times \mathbb{1}(\hat{\gamma}_1^r < \ln rK_{g/f,t-1} \leq \hat{\gamma}_2)$	1.371**	1.317***	-0.054	1.105**	0.001
	(0.628)	(0.471)	(0.559)	(0.519)	(0.497)
$CC \times \mathbb{1}(\ln rK_{g/f,t-1} > \hat{\gamma}_2)$	0.609	0.596	-0.013	0.636	-0.164
	(0.789)	(0.735)	(0.794)	(0.736)	(0.838)
F-Stat H_0: Exogeneity of $\mathbf{P}$	11.09*	18.73***	8.74	11.81*	5.845

Bootstrapped standard errors in parentheses produced from 1,000 block-bootstrapped samples. *** p<0.01, ** p<0.05, * p<0.1. See Appendix C for details about the estimation method. Values (percentiles) of the two thresholds are $\hat{\gamma}_1^r = 1.292$ (47^{th} percentile) and $\hat{\gamma}_2 = 2.198$ (89^{th} percentile) (see Table D2). All regressions include a full vector of unreported year fixed effects, a dummy variable for observations with no fossil fuel patent production ($k_{f,t} = 0$). The set of control variables is: MB: market based policies; CC: command-and-control policies; $\ln EP$: Electricity production (in kW, in logs); $\ln EC$: Electricity consumption per capita (in kW per hour, in logs); EM: electricity import share in domestic production; EX: electricity export share in domestic production; HC: Human capital index;$\ln GDP$: GDP (in thousands of 2011 USD PPP, in logs);$\ln POP$: Population (in logs). Regressions also include unreported control function errors from a first IV stage on policy variable MB and CC.

Appendix A. Modelling the direction of technical change

The theoretical framework is composed of two building blocks. First, we consider a Cobb-Douglas knowledge production function where new knowledge stems from an existing stock of knowledge. We augment it with a policy vector which may spur innovation beyond the role of accumulated scientific knowledge. Second, we introduce heterogeneity in research domains, giving rise to the potential presence of rivalry and spillovers across research domains. Our model builds upon, but is different from, standard models of directed technical change such as Acemoglu et al. (2012). We specifically focus on the innovation production function, our main variables of interest being policy instruments of different nature, in order to better understand how these instruments affect innovation in competing technologies.

The starting point of our analysis is the aggregate Cobb-Douglas knowledge production function augmented with a policy vector $\mathbf{P}$. Abstracting from subscripts i and t accounting for country i at time t, this reads as:

$$k = AK^{\beta_K}\mathbf{C}^{\mathbf{B_C}}e^{\mathbf{B_P}\times\mathbf{P}+\upsilon}, \tag{A1}$$

where k and K represent knowledge flow – or innovation – and knowledge stock – reflecting past innovations. Knowledge flow k is accounted for at the end of a given period of time, whereas the knowledge stock variable K is measured at the beginning of the period considered. A positive coefficient β_K reveals the cumulative nature of the innovative process: new ideas are more likely to emerge from an existing stock of ideas. Policy vector $\mathbf{P}$ accounts for policies, whose effects $\mathbf{B_P}$

represent the core of our investigation (See Section 4). Vector $\mathbf{C}$ includes additional structural factors, which may affect innovation beyond and above the chief role of knowledge stock K and policy vector $\mathbf{P}$. It includes, *inter alia*, human capital, GDP per capita, electricity consumption and production. Parameter υ is composed of time and country fixed effects as well as idiosyncratic shocks that may randomly affect knowledge production. Whereas the knowledge stock variable K is lagged one year, innovation k, vectors $\mathbf{P}$ and $\mathbf{C}$ are contemporaneous.

Equation A1 considers overall knowledge production as a function of overall knowledge stock, irrespective of scientific domains or realm of applications. Thus it is silent on whether policies promote the shift towards one or the other technology domain, nor can it consider potential spillovers across scientific and technical fields. However, often several competing technologies are available. This is the case for low-emission energy innovation, which comprise carbon-free renewable technologies representing a novel and more radical innovation, and fossil-efficient technologies representing an established, incumbent innovation. It is useful to consider two specific domains g and f, respectively.[22] We obtain a system of two equations:

$$\begin{cases} k_g & = A_g K_g^{\beta_{K_g}} K_{-g}^{\beta_{K_{-g}}} \mathbf{C}^{\mathbf{B_{g,C}}} e^{\mathbf{B_{g,P}} \times \mathbf{P} + \upsilon_g} \\ k_f & = A_f K_f^{\beta_{K_f}} K_{-f}^{\beta_{K_{-f}}} \mathbf{C}^{\mathbf{B_{f,C}}} e^{\mathbf{B_{f,P}} \times \mathbf{P} + \upsilon_f} \end{cases} \tag{A2}$$

where K_g (resp. K_f) and K_{-g} (resp. K_{-f}) represents scientific and technological knowledge stocks in realm g (resp. f) and in all other scientific domains excluding realm g (resp. f). Moreover, Model (A2) introduces the possibility of positive spillovers from general knowledge to innovation in realm g and/or f, implying

[22] Hence, $d = \{g; f\}$; g stands for *green* and f stands for *fossil*.

that $\beta_{K_{-g}} > 0$ and/or $\beta_{K_{-f}} > 0$ **[cite]** This also gives rise to the possibility of path dependence where accumulated knowledge reinforces future innovation in the same technological domain. Hence past experience in a domain also reduces the scope for venturing into new fields.

Model (A2) displays the main building blocks of how policies relate with expected outcomes, controlling for past innovation and several additional factors. The presence of two alternative domains, however complementary, raises the issues of policy effectiveness in directing technical change. Following standard theory (Acemoglu et al. 2012), we divide the two equations above. We obtain a reduced-form specification whose estimated set of coefficients can be interpreted as guiding technical change in one specific direction at the expense of the other.

Formally, rewrite $\beta_{K_f} = \beta_{K_g} + \beta_{K_{f'}}$ and substitute this in the second equation pertaining to fossil fuels innovation. Assume further that fields g and f quantitatively represent minor shares of the overall stock of knowledge K, implying that $K_{-g} \simeq K_{-f} \simeq K_{-(g+f)}$, where $K_{-(g+f)} = K - K_g - K_f$. Dividing the first equation pertaining to field g with that pertaining to field f yields:

$$rk = rA \cdot rK^{\beta_{K_g}} \cdot K_f^{-\beta_{K_{f'}}} \cdot K_{-(g+f)}^{\beta_{K_{-(g+f)}}} \cdot \mathbf{C}^{\mathbf{B_C}} \cdot e^{\mathbf{B_P} \times \mathbf{P} + \epsilon}, \tag{A3}$$

where prefix r implies relative values for k, A and K, such that $rk = k_g/k_f$, $rA = A_g/A_f$, and $rK = K_g/K_f$, $\mathbf{B_C} = \mathbf{B_{g,C}} - \mathbf{B_{f,C}}$ and $\mathbf{B_P} = \mathbf{B_{g,P}} - \mathbf{B_{f,P}}$, and $\epsilon = \upsilon_g - \upsilon_f$. Note also that a positive (resp. negative) sign for $\beta_{K_{f'}}$ implies that $\beta_{K_f} > \beta_{K_g}$ (resp. $\beta_{K_f} < \beta_{K_g}$).

The newly defined dependent variable $rk = k_g/k_f$ expresses the direction chosen by a country regarding carbon-free *vs.* carbon-efficient innovation, i.e. higher values of rk imply a stronger commitment towards a radical solution to climate change. Hence another interpretation of rk is that it expresses the direction of innovation towards renewable energy – a path-breaking solution to global warming – relative to fossil-efficient energy – a transitory and incomplete solution to global warming. In a similar fashion, variable $rK = K_g/K_f$ represents the level of accumulated competences in renewable energy sources relative to competence accumulation in fossil fuel energy sources. Higher values of rK imply more specialization towards sustainable growth as opposed to the current paradigm of economic growth.

Model (A3) represents the benchmark of our empirical analysis.

Appendix B. Patent statistics

We use patent data to construct both the dependent variable – which measures the direction of innovative activity – as well as the threshold variable – which measures relative specialization between the two competing technologies.

Patent databases represent a systematic, and nearly exhaustive, source of information about innovative activities across countries and overtime. They gather information on patent holder, assignee location, priority date, and a series of technology classes useful to characterize the technical content of the patent. Since the seminal work of Griliches (1990), patent statistics have been extensively used in the innovation literature (e.g. Jaffe 1986, Audretsch & Feldman 1996, among many others), although they come with certain limitations such as heterogeneity in quality, cross-country differences in patenting incentive criteria (see Archibugi 1992, for a detailed discussion). However, patent statistics is unique in providing information about current and past investments by fined-grained technological domain.

The dependent variable is defined as the ratio of zero-carbon (renewable) to carbon-efficient (fossil fuel) patents in country i and year t. Patent data has been widely used as a proxy for innovation (Griliches 1990, Popp et al. 2010), and one that allows to distinguish between renewable and efficient fossil fuel technologies (Lanzi et al. 2011, Haščič & Migotto 2015). We rely on the Y02E classification generated by the European Patent Office. We extract data from the PATSTAT World Patent Statistics Database, Autumn 2020 version. We select applications to the EPO by any inventor country and earliest filing year, and limit sample to patents which have at least one duplicate in another patenting authority (Haščič et al. 2015, Haščič & Migotto 2015) - that is, we focus on patents with a family size of at least two. Furthermore, being a proxy for innovation, patent statistics inherently capture the effect of past supply-side policies in support of innovation, such as public R&D investments or subsidies for innovation.

We then aggregate patents at the inventor country level distinguishing renewable from efficient fossil-fuel-based technologies. Renewable technologies are solar, wind, geothermal, marine, and hydro as well as technologies for energy generation from biomass and waste. They include patents in subclasses 10/00, namely energy generation through renewable energy sources – geothermal, hydro, oceanic, solar (PV and thermal), wind – as well as 50/00, namely technologies for the production of fuel of non-fossil origin – biofuels and waste. Efficient fossil-fuel-based technologies improve output efficiency (e.g. combined heat and power and combined cycles) and input efficiency (e.g. efficient combustion or heat usage) or allow an efficient electrical power generation and transmission. They encompass patents in subclasses 20/00, namely combustion technologies with mitigation potential – CHP, CCPP, IGCC, synair, cold flame, etc. – and subclass 40/00 Technologies for efficient electrical power generation, transmission or distribution – such as reactive power compensation and super- conductors.[23]

The threshold variable, measuring each country's level of specialization in renewable relative to efficient fossil fuel technologies, is also based on patent statistics. Specifically, for each country and each year we compute the knowledge stocks for both renewable and efficient fossil energy technologies. Following Verdolini & Galeotti (2011), to compute the stock variables, we rely on the perpetual inven-

[23] For a more detailed discussion of the different technologies, please refer to the OECD ENV-TECH classification.

tory method to compute knowledge stocks in renewables and efficient fossil fuel technologies. More specifically, the knowledge stock in domain d is obtained as: $K_{idt} = k_{idt} + (1-\delta)K_{idt-1}$ where we set $\delta = 0.1$. The initial value of the knowledge stock is defined as $K_0 = \frac{k_{idt_0}}{(\bar{g}_s+\delta)}$, with $\bar{r}_d$ being the average rate of growth of patenting in technology domain d for the period between t_0 and $t_0 - 4$. We use $t_0 = 1984$ as the initial year to compute knowledge stock. 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.

Appendix C. Econometric implementation

C.1 Unobserved heterogeneity with slowly changing policy variables

Following previous literature on environmental innovation (Nesta et al. 2014, Aghion et al. 2016), our motivation lies in the fact that, although there is a time variation in the policy variables, such measures change only slowly over time. In such context, the use of within transformations would withdraw a large share of the identifying variation, possibly leading to inconsistent estimates of the parameters of interest $\mathbf{B_P}$ (Blundell et al. 2002). In the presence of pre-sample information, we augment the three models where $PSM_i = \bar{rk}_{ip} = \frac{1}{TP}\sum_{r=0}^{TP-1} rk_{i,0-r}$ represents the pre-sample mean which grasps persistent differences across countries, and TP represents the number of pre-sample years.[24]

C.2 A control function approach to policy endogeneity

A key requirement for a causal interpretation of the policy inducement effects is the exogeneity of the environmental policies variables. This requirement is likely to be violated in our context for at least three reasons. First, policy choices depend upon the expected effectiveness of the policy in terms of both economic

[24] 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.

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 redirect energy innovations. Likewise, efforts by fossil fuel lobbies can damper the policy response depending on the expected policy effect on vested interests. As a result, the policy response will positively depend on the current degree of specialization in energy technologies, leading to an upward bias in the coefficients of interest.[25]

Second, a well-known argument postulates that policy interventions should be temporary and support renewable energy only during an initial phase of technological development, that is, 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). 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. This source of estimation bias counterbalances the previous one, thus it remains an empirical issue to assess which one prevails.

Third, another source of endogeneity arises from errors in the measurement of MB and CC policies. 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

[25]For instance, fossil fuel lobbies have been very powerful to ensure subsidies to fossil fuel extraction, production and research activities. These subsidies, partly unobservable, are expected to be negatively correlated with both green innovation and policies, 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 upwards.

tariffs (Botta & Kozluk 2014). 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.

To address the above concerns related to reverse causality, omitted variable bias and measurement error, we use a control function approach. While such approach is very similar to a classical instrumental variable approach, it is recommended to deal with specifications where the endogenous explanatory variable has a nonlinear effect on the dependent variable (Wooldridge 2015). The basic idea is that the residuals from a first stage regression – in which the policy indicator is regressed over the vector of controls and excluded instruments discussed below– account for policy endogeneity in the second stage by absorbing the part of the policy variation that is correlated with energy innovation.

Building a suitable instrument of policy varying at the country level is challenging since policy variation is affected by several unobservable confounders. In this paper, we propose a leave-one-out instrument that considers for country i a weighted average of environmental policies in countries other than i but sharing the same legal origins (LaPorta et al. 1999). The weights of the instruments are based on a similarity index, calculated as the angular distance (Jaffe 1986), between a vector of institutional characteristics of country i and another country j sharing the same legal origins.[26] Our instrumental variables read:

[26]The vector of institutional characteristics include an index measuring corruption in government, an index rating property rights protection, an index measuring the level of tax compliance and an index of political rights. Detailed description of all these variables as well as the database can be found in LaPorta et al. (1999).

$$\bar{P}_{i,t} = \frac{1}{\sum_N \phi_{i,j}} \sum_{j \neq i} \phi_{i,j} \omega_{i,j} P_{j,t} \tag{C1}$$

where P is either MB or CC, $\phi_{i,j}$ is an indicator set to unity if country i and country j share the same legal origin, and $\omega = \frac{S_i' S_j}{\left[(S_i' S_i)(S_j' S_j)\right]^{1/2}}$ is the uncentered correlation coefficient between the two vectors containing the four indexes of institutional characteristics for any couple of countries i and j in our sample; ω is equal to 1 when i and j have identical institutional characteristics, and equal to zero when they are most dissimilar.

Exploiting similarities between countries of the same legal origin ensures that the instrument is strong and, at the same time, exhibits enough variation, both within and between countries. The exclusion restriction is that the sources of endogeneity are mitigated by considering policy variation in other countries. That is: conditional on country specific controls, the weighted average of the policy variation in other countries except i is not correlated with energy innovation in country i. An example may help understand how the instrument work. Spain, France and Italy share similar institutional characteristics. However, only Spain has a clear leader company in renewable energy innovation, e.g. Gamesa. In turn, France and Italy have two well-established utilities that are adapting to a low carbon economy. The first and second sources of endogeneity are likely to go in opposite direction in those three countries in spite of the fact that those countries share the same institutions. Thus, the instrument is successful in mitigating endogeneity in this case. Basically, the instrument leverages the fact that the energy sector, and thus the source of lobbying in it, is highly heterogeneous across countries sharing the same institutional setup. Recall, however, that in cross-country analyses there is no ideal source of exogenous policy variation, thus the instrumental variable approach should be seen as a way to mitigate rather than fully solve endogeneity problems.

The control function approach to endogeneity implies the use of extra-regressors, our vector of instruments $\bar{\boldsymbol{P}}$, to annihilate the correlation between the endogenous policy variables and the error term in our models of interest. Implementation implies a two-stage process as follows:

$$\mathbf{P} = f(\mathbf{X}, \mathbf{C}) + \boldsymbol{\delta}\bar{\boldsymbol{P}} + \boldsymbol{\nu} \tag{C2}$$

$$\ln rk = f(\mathbf{X}, \mathbf{C}) + g(\mathbf{P}) + \boldsymbol{\rho}\hat{\boldsymbol{\nu}} + \varepsilon \tag{C3}$$

where the first equation represents the first-stage and the second equation represents the second stage, that is, any of Models (2), (3) and (4). Vector $g(\mathbf{P})$ represents the various policy vectors across the linear, interaction and threshold models. The key part here is the inclusion of $\hat{\boldsymbol{\nu}}$ in the main equation. By construction, residual $\hat{\boldsymbol{\nu}}$ ensures that the newly obtained error term of the second equation ε be uncorrelated with $\mathbf{X}$, $\mathbf{C}$, policy vector $\mathbf{P}$ as well as with $\hat{\boldsymbol{\nu}}$: $E((\mathbf{X}, \mathbf{C})'\varepsilon) = 0$, $E(\mathbf{P}'\varepsilon) = 0$, and $E(\hat{\boldsymbol{\nu}}'\varepsilon) = 0$. Importantly, the inclusion of a generated regressor on the left-hand-side implies the use of block-bootstrapped standard errors.

Although two-stage least squares and control function approaches yield the same coefficient, the advantage of relying on the latter is that it allows for a direct test of endogeneity of the policy variable (Wooldridge 2015). In fact a simple joint F-test for vector $\hat{\boldsymbol{\nu}}$ in the second stage allows testing for policy endogeneity. A significant F-statistics would imply that the policy variables are indeed endogenous. The converse would imply exogeneity of the policy variables. We report such endogeneity test for the policy variable at the bottom of the tables of results.

Second, we need to make sure that our set of instruments $\bar{\boldsymbol{P}}$ do bring relevant information in their prediction for $\mathbf{P}$. As prescribed in Angrist & Pischke (2009, p.217), we report the F-statistics pertaining to the first stage equation. The rule of thumb implies that an F-statistics exceeding a value of 10 implies string instruments, legitimating the use of our instruments vector.

C.3 Estimation of thresholds

We rely on the estimation and inference methodology developed by (Hansen 1999) to determine the number of concealed thresholds as well as their values. The key idea is that the algorithm lets the threshold vary incrementally – percentile by percentile – with the threshold variable rK and chooses threshold γ which minimises the sum of squared errors.

In a nutshell, the minimization program starts by estimating a one-threshold model by: (i) sorting the threshold variable rK; (ii) eliminating the smallest and largest 10%. The remaining N values of rK constitute the candidate values γ; (iii) for each of these N values, the algorithm estimates regression (4) to generate the corresponding sum of squared errors; (iv) the smallest value of the latter yields the estimate $\hat{\gamma}$; (v) the preferred value for $\hat{\gamma}$ is used to compare the explanatory power of the one threshold model with that of a model with no threshold; (vi) if the former is preferred over the latter, the value $\hat{\gamma}_1$ is taken as a threshold and the program searches for a second threshold iteratively using the two-thresholds.

Conditional on the existence of a first and a second threshold, a similar procedure is followed to determine whether additional thresholds exist.

To retrieve an estimate of γ, we first define $\mathbf{k}$, the column vector stacking all observations of the dependent variable $\ln rK$; $\hat{\mathbf{k}}(\gamma)$, the corresponding vector of predicted values by estimating Equation (4) and the vector of residuals $\hat{\mathbf{e}}(\gamma) = \mathbf{k} - \hat{\mathbf{k}}(\gamma)$. 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:

$$\hat{\gamma} = \underset{\gamma}{\operatorname{argmin}}\; S_1(\gamma). \tag{C4}$$

The computation of the least squares estimate of the threshold γ involves the minimization exercise C4. To do so, we first sort the threshold variable rK 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 observations represent the set of values over which the optimal $\hat{\gamma}$ is determined. Using Equation in (4), we obtain the sum of squared errors $\hat{\mathbf{e}}(\gamma)$ and its associated $S_1(\gamma)$. The smallest value for $S_1(\gamma)$ determines the threshold value $\hat{\gamma}$.

As previously mentioned, Hansen (1999)'s method can be generalized to any number of thresholds. In the case of two thresholds for example, one strategy could be 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.[27] Rather, Hansen (1999) suggests to

[27] A search grid over (γ_1, γ_2) requires a significant number of regressions. If the search operates on the percentiles of the threshold variables, the search grid that would trim the bottom and

proceed sequentially by taking threshold $\hat{\gamma}_1$ as given and searching for γ_2 over the threshold variable rK by minimizing $S_2(\hat{\gamma}_1, \gamma_2)$.[28] Fixing γ_1 to $\hat{\gamma}_1$, the minimization program to identify the second threshold can be written as:

$$\hat{\gamma}_2 = \underset{\gamma_2}{\text{argmin}}\ S_2\left(\gamma_2\big|_{\gamma_1=\hat{\gamma}_1}\right). \tag{C5}$$

Once the vector of thresholds $\hat{\gamma}$ 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 comparing the model with no threshold as displayed in Eq. 2 with model 4. This is achieved by computing the likelihood ratio test H_0 based on:

$$F_1 = \frac{S_0 - S_1(\hat{\gamma})}{\hat{\sigma}^2}, \tag{C6}$$

Because the distribution of F_1 is non standard and depends upon moments of the sample, critical values for F_1 cannot be tabulated. We therefore follow Hansen (1999) and use the bootstrapped strategy as follows. We first randomly

top 5 percent would require $90^2 = 8,100$ regressions. Because of our relatively small sample size, our search operate on observations rather than percentiles, yielding N^2 regressions. Setting N to 700 as in our case would necessitate 490,000 regressions. Clearly, a search grid for a higher order number of thresholds rapidly becomes prohibitive.

[28]Because it is important to have a minimum number of observations in each regime, we restrict the search over rK so that the distance between $\hat{\gamma}_1$ and $\hat{\gamma}_2$ amounts to at least a decile.

draw with replacement n countries in order to produce a bootstrapped sample of size $N = n \times T$ of errors $\hat{\mathbf{e}}$ from the no-threshold model. We then stack these bootstrapped errors and add them to $\hat{\mathbf{k}}$, where $\hat{\mathbf{k}}$ represents predicted outcome from the model without threshold. Using the bootstrapped sample, we then estimate specifications 2 and 4 and compute the likelihood ratio statistics F_1. We repeat this procedure a sufficiently large number of times and count the number of times for which the simulated statistics for F_1 exceeds the actual one. The share of samples where the simulated F_1 exceeds the original one is used as the critical probability value. The null hypothesis of no threshold is rejected when the p-value is smaller than the desired critical value.[29]

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

$$LR_1(\gamma) = \frac{S_1(\gamma) - S_1(\hat{\gamma})}{\hat{\sigma}^2}, \tag{C7}$$

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).

[29]For models with a number Γ of thresholds, this procedure uses predicted outcome $\hat{\mathbf{k}}$ and residual $\hat{\mathbf{e}}$ with $\Gamma - 1$ thresholds.

Hansen (1999)'s method can be generalized to any higher number of thresholds. Conditional on having identified one threshold, we may then search for a higher number of thresholds.We set the maximum number of possible thresholds to three, implying potentially four types of policy regimes. In the two- and three-threshold models, the likelihood ratio statistics reads, respectively:

$$LR_2(\gamma) = \frac{S_2(\gamma_2) - S_2(\hat{\gamma_2})}{\hat{\sigma}^2}. \tag{C8}$$

and

$$LR_3(\gamma) = \frac{S_3(\gamma_3) - S_3(\hat{\gamma_3})}{\hat{\sigma}^2}. \tag{C9}$$

Last but not least, Hansen's method applies to panel data. We can therefore decompose the error term ϵ into a country fixed effect μ_i, a time fixed effect λ_t, and a residual error term ε_{it}: $\epsilon_{it} = \mu_i + \lambda_t + \varepsilon_{it}$. In this specific application, we amend Hansen's approach in one important way. While Hansen (1999) treats individual fixed effects using a conventional within-transformation, we model the country fixed effect μ_i using the pre-sample mean of the dependent variable. However this estimator is inconsistent for the parameters of interest if the regressors are not strictly exogenous, which is likely to be the case with our policy variables.[30] This is another reason to implementing the Pre-Sample mean as presented in Section C.1.

[30] An alternative is to use the quasi-differenced estimator as proposed by Chamberlain (1992) and Wooldridge (1997). However, the quasi-differenced estimator lacks consistency series are highly persistent.

C.4 Model selection

Our objective is to arbitrate among the various models considered and choose the one specification which most accurately reflects the underlying data generating process (DGP). Because all specifications share some common explanatory variables, we consider them as overlapping models.[31] This rules out the possibility of using both the log-likelihood ratio test for nested models nor Vuong's statistics for strictly non nested models (Vuong 1989). Moreover, the number of explanatory variables differs from one model to another. This screens out the possibility to rely on the simple R-squared and log-likelihood statistics (LL) for model comparisons. Because both vary monotonically with the number of explanatory variables, they cannot provide information on the policy-induced model of innovation closest to the underlying, but unknown, DGP.

Our strategy is to provide three series indicators that all suit model selection with overlapping models. The first indicator is the adjusted R-squared. Its most appealing feature is that its relationship with the number of explanatory variables can either increase or decrease, depending on whether the additional regressor(s) brings valuable information to the model. The adjusted R-squared increases only when the newly added set of variables brings valuable information to the model. It otherwise decreases. Hence one should choose the model with the highest adjusted R-squared. In the same vein, we use Akaike information criterion (AIC) based indicators. Model selection based on the AIC is attractive because, again, its relationship with the number of explanatory variables can either increase or decrease,

[31] This is in fact more subtle. Equations (2) and (3) represent the classical case of nested models, where Equation (2) is nested into Equation (3), with the parameter for the interaction term being constrained to nullity ($\mathbf{B}_{\mathbf{K_g},\mathbf{P}} = 0$). However, the threshold specification, regardless of the number of thresholds, is not nested into the other two specifications.

depending on whether the additional regressor(s) brings valuable information to the model.[32] The AIC decreases only when the newly added set of variables brings valuable information to the model. It otherwise increases. Hence one should choose the model which minimizes AIC. Additionally, we use a modified version of AIC, AIC_c, which corrects for small samples, as is the case here.[33]

Given the additional complexity implied by the threshold specification, we must provide some intuition about the potential gain in fitting the data implied by using a more complex specification. This is why we find it necessary to provide additional information regarding the significance in the gap in scores across models. As such, AIC and AIC_c are hard to interpret, but both can be used to derived more intuitive measures of strength of evidence in favor of one better model. Following Burnham & Anderson (2004), the simple transformation $\exp(-\frac{\triangle}{2})$, where $\triangle = AIC_m - \min(AIC)$ or $\triangle_c = AIC_{c,m} - \min(AIC_c)$ and m is the given model being evaluated, can be interpreted as the likelihood of the model, given the data.[34] Another indicator is to use Akaike weights $\omega_m = \frac{\exp(-\frac{\triangle_m}{2})}{\sum_m \exp(-\frac{\triangle_m}{2})}$ and can be interpreted as weights of evidence in favor of model m.

Last, we rely on Vuong's $2LR$ statistics for overlapping models (Vuong 1989). Vuong's $2LR$ statistics is a two-by-two model comparison by taking the usual log's ratio statistics: $2 \times (LL(\mathbf{F}) - LL(\mathbf{G}))$, where $\mathbf{F}$ and $\mathbf{G}$ refer to overlapping specifications displayed in Equations (2), (3), (4) and (5). Unlike the LR-test for nested models, Vuong's $2LR$ can be either positive or negative. A positive value indicates that $LL(\mathbf{F})$ exceeds $LL(\mathbf{G})$, so that model $\mathbf{F}$ must be preferred over $\mathbf{G}$.

[32] The Akaike criterion reads $AIC = -2LL + 2K$ (where K is the number of parameters).

[33] The corrected version reads $AIC_c = -2LL + 2K + \frac{2K(K+1)}{n-K-1}$ (where n is the number of observations). AIC_c shares the same features as AIC.

[34] It appears immediately that the model yielding the minimum AIC (respectively AIC_c) will also be the one with a likelihood amounting to unity, since $AIC_m - \min(AIC) = 0$.

Conversely, a negative value indicates that $LL(\mathbf{G})$ exceeds $LL(\mathbf{F})$, so that model $\mathbf{G}$ is to be preferred over $\mathbf{F}$. The difficulty is that the asymptotic properties of Vuong's $2LR$ statistics to define a critical probability are difficult to derive. To overcome this limit, we proceed by block bootstrapping on countries, estimate the various candidate models for each bootstrapped sample, compute $LL(\mathbf{F})$ and $LL(\mathbf{G})$, and derive Vuong's $2LR$ statistics. Repeating this experiment for 1,000 bootstrapped samples, we then simply count the number of times Vuong's $2LR$ statistics is positive or negative. The share of positive $2LR$ (resp. negative $2LR$) can be used as a critical probability for the one-sided test in favor of model $\mathbf{F}$ (resp. model $\mathbf{G}$).

Taking stocks of the above, model selection for overlapping models is based on three criteria: the adjusted R-squared, AIC-based criteria $\triangle$ and ω, and Vuong's $2LR$ statistics for overlapping models. Bear in mind that, because $2LR(\mathbf{F}, \mathbf{H}) = 2LR(\mathbf{F}, \mathbf{G}) + 2LR(\mathbf{G}, \mathbf{H})$[35], $2LR$ distances are cumulative, so that our conclusion on the dominance of a model over another one are transitive. Hence, instead of comparing all possible pairwise comparisons, we perform three comparisons only.

[35]More precisely, $2LR(\mathbf{F}, \mathbf{G}) + 2LR(\mathbf{G}, \mathbf{H}) = 2 \times (LL(\mathbf{F}) - LL(\mathbf{G})) + 2 \times (LL(\mathbf{G}) - LL(\mathbf{H})) = 2 \times (LL(\mathbf{F}) - LL(\mathbf{H})) = 2LR(\mathbf{F}, \mathbf{H})$.

Appendix D. Ancillary results

D.1 Quality of instruments

Table D1 below report the results of first stage regressions for all policies taken at once ALL, CC and MB. Because all our policy measures are normalized such that they belong the the $[0-1]$ interval, we rely on the use of Tobit regression to account for left and right censorship in the data. Focusing on coefficient pertaining to our instrument, we observe a positive and significant relationship between policies implemented in a given country and those implemented in similar countries with same legal origin. In other words, policies carried out in countries with the same legal origin and a high index of similarity are good predictors for local implementation. Observe, however, that this holds *within* policy types: neighbouring CC policies correlate with local CC ones, and neighboring MB policies correlate with local MB ones).[36] We find no sign of fertilization across policies. In Column 2 in fact, neighbouring CC policies negatively correlated with the implementation of local MB policies. The interpretation of such negative effect is far from immediate. A possible interpretation is that countries where MB policies are high believe that market-based incentives suffice in organizing the transition, and compete with their neighbour countries on this ground alone. We find no sign of neighbouring MB policies affecting local CC policies.

[36] This also holds when we compile all policies within one broad ALL category, as is exposed in Column 1.

Table D1: First Stage Tobit Regressions

	(1)	(2)	(3)
	ALL	*MB*	*CC*
Pre-sample mean	0.061***	0.086***	0.057**
	(0.018)	(0.025)	(0.023)
$\ln rK_{g/f,t-1}$	0.013	0.147***	-0.041***
	(0.011)	(0.019)	(0.016)
$\ln K_{f,t-1}$	0.033**	0.158***	-0.022
	(0.013)	(0.025)	(0.018)
$\ln K_{-(g+f),t-1}$	-0.023**	-0.129***	0.024*
	(0.010)	(0.019)	(0.014)
$\bar{\boldsymbol{P}}_{ALL}$	0.880***		
	(0.070)		
$\bar{\boldsymbol{P}}_{MB}$		1.441***	0.063
		(0.175)	(0.140)
$\bar{\boldsymbol{P}}_{CC}$		-0.230**	0.912***
		(0.109)	(0.078)
Control variables	Yes	Yes	Yes
Observations	759	759	759
Observations left censored	85	280	132
Observations right censored	0	1	8
F-stat IV	70.51	45.73	65.94

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All regressions include a full vector of unreported year fixed effects, a dummy variable for observations with no fossil fuel patent production ($k_{f,t} = 0$). The set of control variables is: MB: market based policies; CC: command-and-control policies; $\ln EP$: Electricity production (in kW, in logs); $\ln EC$: Electricity consumption per capita (in kW per hour, in logs); EM: electricity import share in domestic production; EX: electricity export share in domestic production; HC: Human capital index;$\ln GDP$: GDP (in thousands of 2011 USD PPP, in logs);$\ln POP$: Population (in logs).

D.2 Number of thresholds

Table D2 presents the estimated thresholds. Hansen's method detects two thresholds in our sample. The point estimates of the two thresholds are 1.292 and 2.198, which correspond to, respectively, the 47^{th} and 89^{th} percentiles of the distribution of the (log-transfomed) $rK_{g/f,t-1}$ threshold variable. The confidence intervals around the estimated thresholds are small, indicating little uncertainty about the location of the level of $rK_{g/f,t-1}$ needed to switch from one regime to another. The plots of the concentrated likelihood ratio function, which are shown in Figure D1, 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 47^{th} percentile of the threshold variable, and a second major fall in the LR at the 89^{th} percentile.

Table D2 also presents the F-statistics for the models. The F-statistics in the column $\hat{\gamma}_1^r$ tests the null hypothesis H_0 of absence of thresholds against the alternative hypothesis H_1 that there is at least one threshold. Similarly, the F-statistics in the column $\hat{\gamma}_2^r$ (resp., $\hat{\gamma}_3^r$) tests the null hypothesis H_0 that there are two (respectively, three) thresholds against the alternative hypothesis H_1 that there is one (respectively, two) thresholds. The F-statistics for the one threshold and two thresholds models are highly significant, with bootstrapped p-values of 0.001, and 0.0104, respectively. Conversely, the F-test for the three-threshold model is not significant, with a bootstrap p-value of 0.126.

The identification of two thresholds is a first indication that the impact of the CC and MB policy instruments on the direction of innovation switches discontinously depending on a country's degree of relative specialization in renewable and

Table D2: Threshold percentile, value, and significance test for the threshold variable $\ln K_{g/f}$

	$\hat{\gamma}_1^r$	$\hat{\gamma}_2$	$\hat{\gamma}_3$
Threshold percentile	47	89	32
Threshold value for $\ln rK_{g/f,t-1}$	1.292	2.198	1.033
95 % CI for $\ln rK_{g/f,t-1}$	[0.929, 1.336]	[2.161,NA]	[.457, 1.154]
90 % CI for $\ln rK_{g/f,t-1}$	[1.219, 1.336]	[2.147,NA]	[.491, 1.120]
F-statistics	25.29	21.42	10.14
P-value	0.001	0.010	0.126

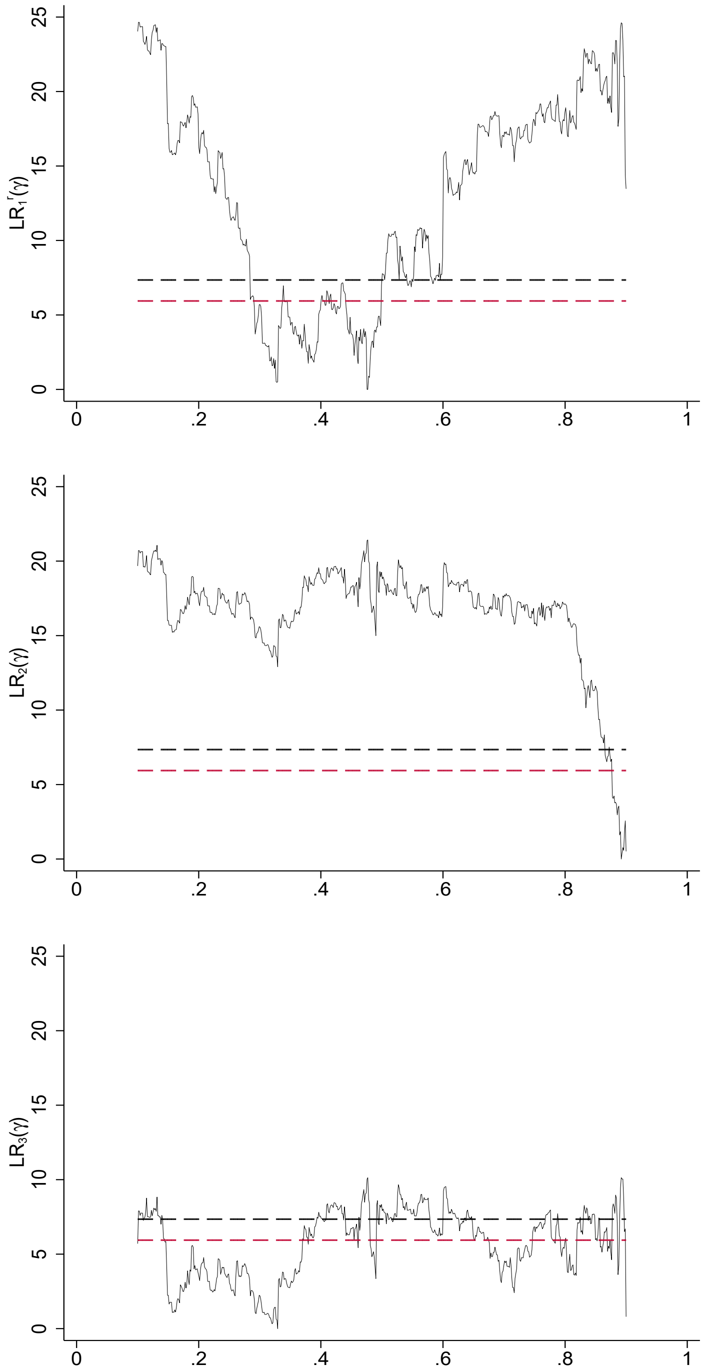
The obtained thresholds are estimated from model 5 of Table 3 with 1000 bootstrapped samples.

fossil-based energy technologies. Table D2 establishes the existence of thresholds in policy effectiveness which depend on the level of the relative specialization in one of the two technological options, against the alternative that policy effectiveness is stable irrespective of specialization. This indicates that the linear model underperforms both the interaction and the threshold models; specifically, the presence of two thresholds implies the existence of three distinct regimes.

D.3 Robustness check

Table D3 displays the results of our various models with a new definition of renewable patents including energy invention in the realms of energy storage and smart grids (Robustness check 1). It also displays the newly estimated thresholds. By and large, the results are consistent with those presented in Table 3. We detect three regimes, with two thresholds located at the 40^{th} and the 89^{th} percentiles of the relative specialization variable $rK_{g/f}$. In Robustness check 2, we use the former definition of renewable patents and increase the quality threshold to family size 4. Again, the results are strikingly consistent with those presented in Table

Figure D1: 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.



3. We detect three regimes, with two thresholds located at the 68^{th} and the 89^{th} percentiles of the relative specialization variable $rK_{g/f}$. The increase of the first threshold should be no surprise, as increases in the quality threshold of patents forces countries to sharper specialization into renewable patent production.

In both cases, the results of the two-threshold model strongly support the view of discontinuous policy effects across the different regimes: both MB and CC policies bear on the direction of technical change in energy innovation. CC policies act as the *steering wheel* in directing energy innovation towards renewables for countries with a low level of initial competencies in renewable energy innovation. Once a given threshold of specialization is reached, implementing MB policies allows countries to pick up speed in their effort to promote renewable energy innovation.

Table D3: Regressions using alternative definition of patents

	Robustness check 1			Robustness check 2		
Pre-Sample mean	0.157	0.178	0.166	0.327	0.359*	0.345*
	(0.209)	(0.203)	(0.207)	(0.228)	(0.209)	(0.203)
$\ln rK_{g/f,t-1}$	0.433***	0.213	0.271**	0.495***	0.295**	0.365***
	(0.124)	(0.130)	(0.124)	(0.145)	(0.134)	(0.122)
$\ln K_{f,t-1}$	-0.029	-0.021	-0.032	0.108	0.011	0.085
	(0.116)	(0.109)	(0.116)	(0.115)	(0.087)	(0.108)
$\ln K_{-(g+f),t-1}$	0.142	0.142*	0.159*	-0.021	0.010	0.010
	(0.093)	(0.086)	(0.090)	(0.089)	(0.092)	(0.088)
MB policies	0.318	-1.372**		0.076	-1.905***	
	(0.417)	(0.664)		(0.392)	(0.719)	
$MB \times \ln rK_{g/f,t-1}$		0.753*			1.256***	
		(0.453)			(0.466)	
CC policies	1.181**	0.700		1.523**	1.562**	
	(0.527)	(0.644)		(0.601)	(0.736)	
$CC \times \ln rK_{g/f,t-1}$		0.415			-0.134	
		(0.367)			(0.331)	
$MB \times \mathbb{1}(\ln rK_{g/f,t-1} \leq \hat{\gamma}_1^r)$			-0.581			-0.504
			(0.581)			(0.583)
$MB \times \mathbb{1}(\hat{\gamma}_1^r < \ln rK_{g/f,t-1} \leq \hat{\gamma}_2)$			-0.057			0.267
			(0.441)			(0.514)
$MB \times \mathbb{1}(\ln rK_{g/f,t-1} > \hat{\gamma}_2)$			1.143			2.472**
			(1.072)			(1.106)
$CC \times \mathbb{1}(\ln rK_{g/f,t-1} \leq \hat{\gamma}_1^r)$			0.839*			1.472**
			(0.504)			(0.674)
$CC \times \mathbb{1}(\hat{\gamma}_1^r < \ln rK_{g/f,t-1} \leq \hat{\gamma}_2)$			1.353**			1.523**
			(0.571)			(0.635)
$CC \times \mathbb{1}(\ln rK_{g/f,t-1} > \hat{\gamma}_2)$			1.071			0.063
			(0.984)			(1.032)
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	759	759	759	759	759	759
R-squared	0.647	0.666	0.669	0.637	0.652	0.657
LL	-614.9	-594.5	-590.3	-650.5	-633.7	-628.9
RSS	224.6	212.9	210.5	246.7	236.0	233.1
Vuong's $2LR$		40.86	8.312		33.69	9.555
First Threshold			40			68
P-value First threshold			0.002			0.000
Second Threshold			89			89
P-value Second threshold			0.023			0.050

In robustness check 1, we count energy invention in the realms of energy storage and smart grids as renewable patents, and keep family size 2 as the quality threshold. In robustness check 2, we use the former definition of renewable patents and increase the quality threshold to family size 4. Bootstrapped standard errors in parentheses produced from 1,000 block-bootstrapped samples. *** p<0.01, ** p<0.05, * p<0.1. Vuong's ratio $2LR$ statistics for partially overlapping models compares the current specification with the specification of the previous column. All regressions include a full vector of unreported year fixed effects, a dummy variable for observations with no fossil fuel patent production ($k_{f,t} = 0$), and a set of control variables (See Table 3 for a list of control variables. Regressions also include unreported control function errors from a first IV stage on policy variable MB and CC.

Appendix E. Simulations

The model simulates patent production in both renewable and fossil fuels respectively. We choose to simulate patent production, more than the ratio of the two realms of energy innovation, in that actors produce patents irrespective of the ratio. Thus we simulate how actors react to policies in their production of innovation. The direction of innovation is then seen a second order product of innovation itself, although the policy objective is to orientate innovation in a given direction. Therefore, the simulation is based on the following two equations:

$$\begin{cases} \ln \tilde{k}_g & = \hat{\mathbf{B}}_{\mathbf{g},\mathbf{P}}\mathbf{P} + \hat{\beta}_{g,K_f}\tilde{K}_{f,t-1} + \hat{\beta}_{g,rK}\ln r\tilde{K}_{g/f,t-1} + \hat{\mathbf{B}}_{\mathbf{g},\mathbf{C}}\bar{\mathbf{C}} \\ \ln \tilde{k}_f & = \hat{\mathbf{B}}_{\mathbf{f},\mathbf{P}}\mathbf{P} + \hat{\beta}_{f,K_f}\tilde{K}_{f,t-1} + \hat{\beta}_{f,rK}\ln r\tilde{K}_{g/f,t-1} + \hat{\mathbf{B}}_{\mathbf{f},\mathbf{C}}\bar{\mathbf{C}} \end{cases} \tag{E1}$$

where $\hat{\mathbf{B}}$ denotes the vector of estimated coefficients in the renewable (g) or in the fossil fuel (f) equations, respectively. Variables $\tilde{k}$ and $\tilde{K}$ represent recursively simulated realizations of knowledge flow k and knowledge stocks K. Subscript $(t-1)$ implies that all knowledge stock variables are lagged one year. Expression $\hat{\mathbf{B}}_{\mathbf{P}}\mathbf{P}$ is the condensed form of the two-threshold specification, similar to equation 5. Hence their values are those displayed in Columns (5) and (6) of Table 5. Vector $\bar{\mathbf{C}}$ represents all control variables set to their country-specific averages. This implies that the simulated dynamics can only be attributed to variations in policy choices $\mathbf{P}$. Consistently with econometrics results, we define three policy regime R_1, R_2 and R_3. The first regime is characterized as CC policies supporting innovation in renewables, whereas MB policies support innovation in carbon-efficient technologicies ($\mathbf{P}^{\star}_{R1} = \{CC\}$). The second regime implies the reliance on both types of policies ($\mathbf{P}^{\star}_{R2} = \{CC; MB\}$). The third regime is based on the implementation of MB policies exclusively ($\mathbf{P}^{\star}_{R3} = \{MB\}$).

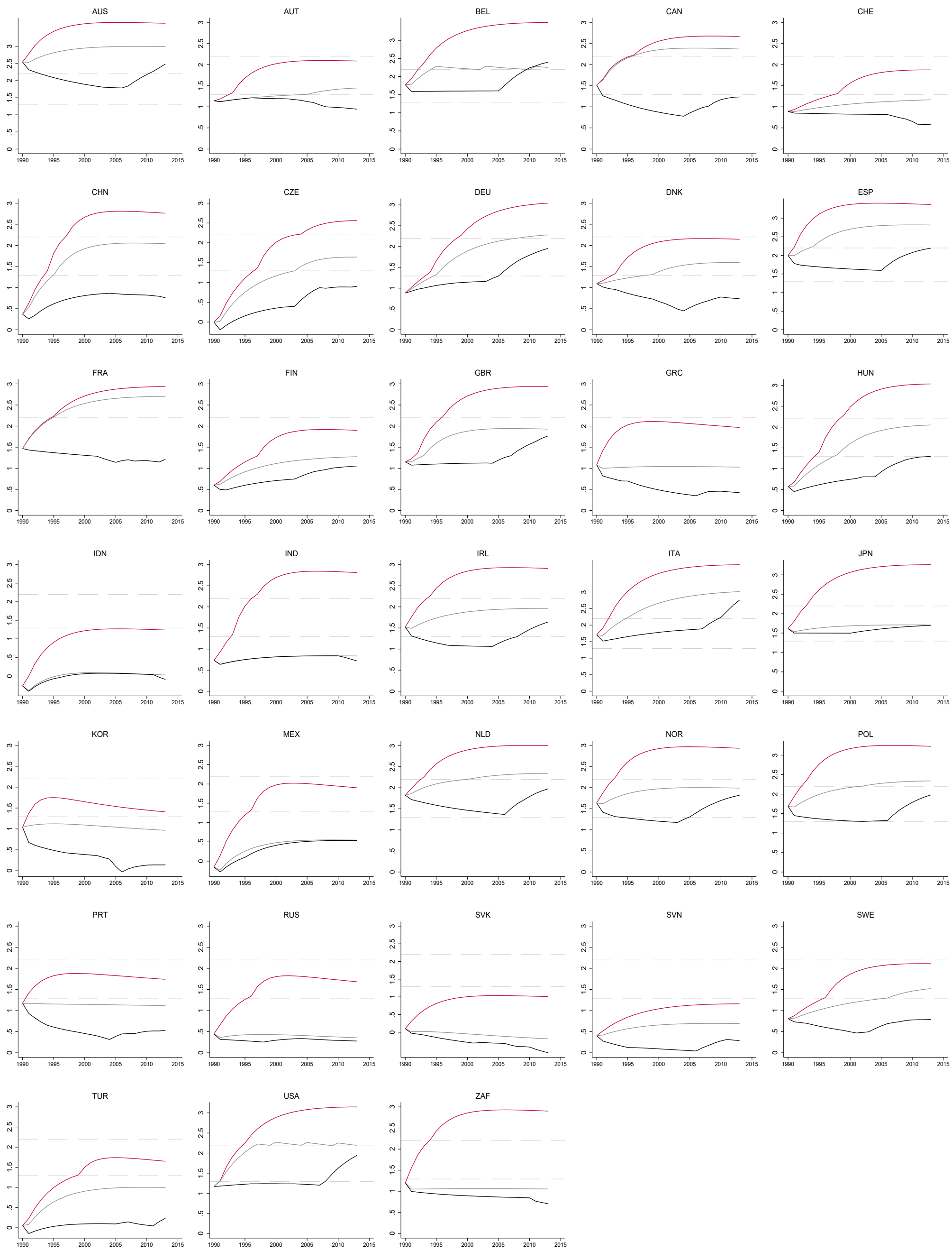
We define policy vector $\mathbf{P}$ as being composed of policy stringency in both CC and MB policies such that $\mathbf{P} = \{S_{CC}; S_{MB}\}$. Policy vector $\mathbf{P}$ is determined in three different ways, leading to three different set of results. First, we define $\mathbf{P_{obs}}$ as the observed policy stringency in a given country, as provided in the data: $\mathbf{P_{obs}} = \{S^{obs}_{CC}, S^{obs}_{MB}\}$. Second, we define $\mathbf{P}^{\star}_{\mathbf{obs}}$ as the *appropriate* policy vector activated under the *adequate* policy regime, with policy intensity set at the observed country's maximum values. Hence $\mathbf{P}^{\star}_{\mathbf{obs},R1} = \{S^{max_i}_{CC}; 0\}$ in regime 1, $\mathbf{P}^{\star}_{\mathbf{obs},R2} = \{S^{max_i}_{CC}; S^{max_i}_{MB}\}$ in regime 2, and $\mathbf{P}^{\star}_{\mathbf{obs},R3} = \{0; S^{max_i}_{MB}\}$ in regime 3. Third, we define $\mathbf{P}^{\star}$ as the *appropriate* policy vector with stringency set to unity, implying that countries design their policy at full steam. This implies that CC policies are active and set at their maximum during the first and second regime only, and that M policies become active only when the third regime has been reached. Conversely, the inappropriate policy is set to zero. Hence $\mathbf{P}^{\star}_{R1} = \{1; 0\}$ in regime 1, $\mathbf{P}^{\star}_{R2} = \{1; 1\}$ in regime 2, and $\mathbf{P}^{\star}_{R3} = \{0; 1\}$ in regime 3.

The simulations run in a recursive manner as follows: (i) In period 0, we set $\tilde{K}_{g,t_0} = K_{g,1990}$, $\tilde{K}_{f,t_0} = K_{f,1990}$; ($ii$) Given $\tilde{K}_{g,t_0}$ and $\tilde{K}_{f,t_0}$, we compute ratio $r\tilde{K}_{g/f,t_0}$ and $\ln r\tilde{K}_{g/f,t_0}$; (iii) variable $\ln r\tilde{K}_{g,t_0}$ is compared to $\hat{\gamma}^{r}_{1}$ and $\hat{\gamma}_2$ in order to determine the policy regimes $\mathbf{P}^{\star}_{\mathbf{obs}}$ and $\mathbf{P}^{\star}$; (iv) simulation Model (E1) uses $\mathbf{P_{obs}}$, $\mathbf{P}^{\star}_{\mathbf{obs}}$ and $\mathbf{P}^{\star}$ to produce expected innovation in the following period (t_1) in renewable energy ($\tilde{\mathbf{k}}_{\mathbf{g}} = \{\tilde{k}^{\mathbf{P_{obs}}}_{g,t_1}; \tilde{k}^{\mathbf{P}^{\star}_{\mathbf{obs}}}_{g,t_1}; \tilde{k}^{\mathbf{P}^{\star}}_{g,t_1}\}$) and in fossil fuel energy ($\tilde{\mathbf{k}}_{\mathbf{f}} = \{\tilde{k}^{\mathbf{P_{obs}}}_{f,t_1}; \tilde{k}^{\mathbf{P}^{\star}_{\mathbf{obs}}}_{f,t_1}; \tilde{k}^{\mathbf{P}^{\star}}_{f,t_1}\}$); ($v$) The vector of patent flow $\tilde{\mathbf{k}}_{\mathbf{g}}$ and $\tilde{\mathbf{k}}_{\mathbf{f}}$ is then added to the vector of accumulated patent stocks $\tilde{\mathbf{K}}_{\mathbf{g}}$ and $\tilde{\mathbf{K}}_{\mathbf{f}}$; ($vi$) new ratios $\mathbf{r}\tilde{\mathbf{K}}_{\mathbf{g/f}} = \{r\tilde{K}^{\mathbf{P_{obs}}}_{g/f,t_1}; r\tilde{K}^{\mathbf{P}^{\star}_{\mathbf{obs}}}_{g/f,t_1}; r\tilde{K}^{\mathbf{P}^{\star}}_{g/f,t_1}\}$ and their corresponding log-transformed values are computed as in (*ii*). The simulation then loops over (*iii*)-(*vi*) until t_{22} is reached, which is the simulated equivalent for year 2012.

Under the three policy scenarios, we produce three series $\mathbf{r\tilde{K}_{g/f}}$. The first captures the direction of innovation implied by the actual policy mix ($\mathbf{P_{obs}}$). The second captures how the direction of innovation would have been affected, had the country abided by the right timing and at its actual policy stringency ($\mathbf{P^{\star}_{obs}}$). The third captures how the direction of innovation would have been affected, had the country abided by the right timing (given its level of relative specialization) as well as implemented the highest policy stringency ($\mathbf{P^{\star}}$).

Figure E1 provides the simulated dynamics of the renewable to fossil-fuel patent stock $\ln rK$ using Equation E1 for all countries. The displayed dynamics is for the specialization variable $\ln r\tilde{K}_{g/f}$ displayed, using alternatively $\mathbf{P_{obs}}$ (black line), $\mathbf{P^{\star}_{obs}}$ (grey line), and $\mathbf{P^{\star}}$ (red line). The dashed horizontal grey lines denote the first ($\hat{\gamma}_1$) and second ($\hat{\gamma}_2$) thresholds.

Figure E1: Simulating the country dynamics of the renewable to fossil-fuel patent stock under alternative policy scenarios



Specialization variable $\ln r\tilde{K}_{g/f}$ displayed, using alternatively $\mathbf{P_{obs}}$ (black line), $\mathbf{P^{\star}_{obs}}$ (grey line), and $\mathbf{P}^{\star}$ (red line). The dashed horizontal grey lines denote the first ($\hat{\gamma}_1$) and second ($\hat{\gamma}_2$) thresholds.

ABOUT OFCE

The Paris-based Observatoire français des conjonctures économiques (OFCE), or French Economic Observatory is an independent and publicly-funded centre whose activities focus on economic research, forecasting and the evaluation of public policy.

Its 1981 founding charter established it as part of the French Fondation nationale des sciences politiques (Sciences Po) and gave it the mission is to "ensure that the fruits of scientific rigour and academic independence serve the public debate about the economy". The OFCE fulfils this mission by conducting theoretical and empirical studies, taking part in international scientific networks, and assuring a regular presence in the media through close cooperation with the French and European public authorities. The work of the OFCE covers most fields of economic analysis, from macroeconomics, growth, social welfare programmes, taxation and employment policy to sustainable development, competition, innovation and regulatory affairs.

ABOUT SCIENCES PO

Sciences Po is an institution of higher education and research in the humanities and social sciences. Its work in law, economics, history, political science and sociology is pursued through ten research units and several crosscutting programmes.
Its research community includes over two hundred twenty members and three hundred fifty PhD candidates. Recognized internationally, their work covers a wide range of topics including education, democracies, urban development, globalization and public health.
One of Sciences Po's key objectives is to make a significant contribution to methodological, epistemological and theoretical advances in the humanities and social sciences. Sciences Po's mission is also to share the results of its research with the international research community, students, and more broadly, society as a whole.

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