This work is under progress.

Environmental Policies, Institutional Quality, and Green Innovation*

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Abstract. In this article, I estimate the impact of environmental policies on environment-friendly patents. This study contributes to the literature by investigating the joint effect of environmental policy stringency with institutional quality. Panel data covers 31 countries from 1990 to 2019. Due to the count nature of patent data my model has a Poisson distribution. I use a pre-sample mean estimator to control for country fixed effects and to deal with heterogeneity among countries. Contrary to the induced innovation hypothesis, increased oil and electricity prices do not necessarily cause to more green innovation at the country-level. In line with scholars who emphasize the necessity of government intervention to tackle climate change, countries with more stringent policies, and bureaucratic quality perform better innovative activity in environment-friendly technologies. Finally, using instrumental variable strategy with control function approach confirms that the effect of policies on innovation is causal.

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1. Introduction

Growing crisis on the climate change shows an immediate need for innovation in green technologies. Dealing with global challenges on environment is possible with developing alternative energy sources. There is an urgent need of technologies which uses fewer resources with fewer greenhouse gas emission. Countries rise their pledges on clean environment-related goals, but efforts are not sufficient because meanwhile market failure brings in negative externalities on environment. In that regard, government intervention through green industrial policies is recalled by scholars (i.e. Rodrik (2014)). For instance, Acemoglu et al. (2012) proposed the directed technical change to reorient the innovation from dirty to clean inputs because there is an excess R&D spending on dirty innovation. Such intervention moderates the production cost in clean innovation. Putting state intervention into center stage reminds the significant role of institutional frameworks.

Literature uses two policy instruments while investigating the determinants of green innovation. First, it focuses on the energy pricing. Induced innovation hypothesis claims that increased energy prices redirect innovators towards energy-efficient technologies (Popp, 2002). Other studies also support the induced innovation both at firm/industry-level (Aghion et al., 2016; Newell et al., 1999) and country-level (Johnstone et al., 2010). Second, it empirically analyzes the catalyzer role of environmental policies on green innovation. However, institutional environment as a necessary condition for successful policy implementation is surprisingly limited. Nesta et al. (2014) take into consideration competition/market liberalization and show its mediator role in green innovation. Fabrizi et al. (2018) find that the positive impact of environmental policies is conditional on the network participation among European Union countries.

This study fills the gap by revealing the complementary roles between policies and institutional environment on green innovation. It claims that both environmental policies and institutional quality cause to innovation in environment-friendly technologies. It also expects policies are more effective with better institutions. I use International Country Risk Guide's (ICRG) political variables as proxy for institutional quality. Depending on availability of the data, I cover 31 countries between 1990 to 2019. Because of the count structure of patent data as dependent variable, my model has Poisson distribution. To tackle heterogeneity in panel setting, I employ presample mean scaling estimator to control for fixed effects (Blundell et al., 1999). To deal with possible endogeneity bias I implement instrumental variable strategy with a control function approach.

I find a significant and positive impact of environmental policies and institutions on green innovation. Their joint effect does not necessarily result in more innovation. Findings are robust to controlling for R&D spending, which is the main input for an innovative outcome. Alternative variables and models also provide strong and robust results. Finally, using democratic durability as an instrument on policies, I show that the effect of policies on innovation is causal and not due to self-selection.

The rest of the paper is organized as follows. Section 2 presents the literature on induced innovation, green policies, and institutions. It then makes a connection between them and builds hypothesis. Section 3 explains the data, and econometric models. Section 4 discusses the findings and Section 5 concludes.

2. Factors Behind the Green Innovation

2.1. Environmental Policies

How innovators respond to environmental policies has received a growing attention recently. Market failure produces negative externalities on the environment due to insufficient clean innovation and too much R&D expenditure on dirty technologies. Theoretical models of climate change with endogenous technical change present some solutions (Buonanno et al., 2003). For instance, Acemoglu et al. (2012) argue that carbon taxes and research subsidies on clean inputs can redirect the innovation from dirty to clean technologies.

Two measurements are applied for policies at the country level research that are environmental policy stringency (EPS) and R&D expenditure. Broad literature finds positive impacts of environmental policies and environment-related R&D spending on environmental patents (Johnstone et al., 2010; Nesta et al., 2014; Johnstone et al., 2012; Fabrizi et al., 2018; Sterlacchini, 2020). Positive impact of EPS is also found in green productivity (Wang et al., 2019).

Hypothesis 1. More stringent environmental policies, higher the green innovation.

2.2.Institutional Quality

Acemoglu et al (2012) emphasize a temporary government intervention to redirect the innovation from dirty to clean technologies under laissez-faire. Similarly, Rodrik (2014) points out the need for an institutional design while accomplishing the green industrial policies. He carries three ideas on which green industrial policies should be built that are embeddedness, discipline and accountability between public and private sectors. Putting the government intervention again at the center stage in the short or long term reminds us of the importance of institutional environment[1].

Studies on the role of institutions on green technology innovation have an increasing trend. Zhao et al. (2021) find that increased financial risk[2] directly reduces CO_2 emissions and increases technological innovation. In addition, Chaudhry et al. (2021) show that

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[1] Rodrik (2014) provides the example of South Korea's developmental state model while explaining those three key ideas behind the industrial policy design. More literature on the role of institutions in East Asian developmental states can be found via (Crafts, 1999; Ahmad and Hall, 2012; Rock, 2013; Keefer, 2011; Ito and Chinn, 2007). These studies mostly use ICRG indicators in the empirical analysis including bureaucratic quality, corruption, law, and accountability measurements.

[2] They use Financial Risk Rating from ICRG.

institutions[3] have negative impact on environmental indicators. Moreover, Sun et al. (2019) examine the support of reliable government institutions[4] for adopting green technology. Lastly, while measuring the impact of terror indices in innovation of renewables technologies, Zheng et al. (2021) control for domestic institutional variables[5].

Based on the existing literature which includes various institutional variables, I prefer to use bureaucratic quality as a proxy for institutions. Environmental policies require long-term implementation of policies. Institutional framework in terms of continuation of policy implementation is important. Change in governance should not cancel the policies. Bureaucratic quality index from ICRG is defined as how institutions absorb the shock and minimize the revision of policies due to the change in governments.

Hypothesis 2. Better bureaucratic quality, higher the green innovation.

2.3.Conditional impact of policies on institutions

Environmental policies are expected to be more efficient when conducted in well-designed institutional environment. It is because implementation of those policies requires long-term and stable political medium, as well as economic and social support. Two studies investigate the joint effects of policies and institutional environments. First, Nesta et al. (2014) estimate the impact of policies on innovation under competitive markets. They find that renewable energy policies are more effective in countries with liberalized energy markets. Second, Fabrizi et al. (2018) estimate the conditional impact of policies with network participation. They show that market-based regulation policies and participation in green research networks have complementary role in environmental innovation. In a similar vein, this study aims to investigate the joint effects of green policies and institutions on green innovation.

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[3] They compose an institution index from five indicators of ICRG.
[4] They combine five categories from the World Economic Freedom Index for the institutional quality.
[5] They use stability and corruption from ICRG.

Hypothesis 3. Policies implemented with higher bureaucratic quality, higher the green innovation.

2.4.Induced Innovation

Another motivation behind the innovator's reorientation towards green technologies is the change in prices. Hicks (1932) introduced the induced innovation hypothesis that rise in factor prices leads to the need in innovation which does not use those expensive inputs. An early work which tests Hicks' hypothesis is conducted by Newell et al. (1999) on air-conditioning industry. Next, Popp (2002) estimates the effect of energy prices on the energy-efficient innovation. Aghion et al. (2016) find similar results for the auto industry that increased fuel prices cause firms to innovate in clean technologies. Cross-country studies use electricity price (Nesta et al., 2014; Johnstone et al., 2010) and oil prices (Sterlacchini, 2020) on green patents and find mix results. In this study I include both electricity prices and crude oil import prices and expect to find positive affect of them on green innovation.

Hypothesis 4. Higher the energy prices, higher the green innovation.

3. Empirical Models

3.1. Data and Descriptive Statistics

I use the OECD's patent data for environment-friendly technologies as the dependent variable. I use patens filed under the Patent Cooperation Treaty (PTC) for baseline estimations and triadic patent families for the robustness checks. OECD derives the data from Worldwide Patent Statistical database, PATSTAT. Patent data is available from 1976 to 2019. Depending on the availability of all variables, the panel dataset covers the period of 1990-2019 for 31 countries. Table for country list can be found in Appendix. Figure 1 presents the trends on patents for the World. Patents including all technology domains have an increasing trend since 1980s whereas environment-related technologies rise after 1990s. Triadic families are obviously fewer than patents filed under PTC. Figure 2 focuses on only environment-friendly patens filed under PTC. United States, Germany, Japan, South Korea, and China are leading countries in green innovation.

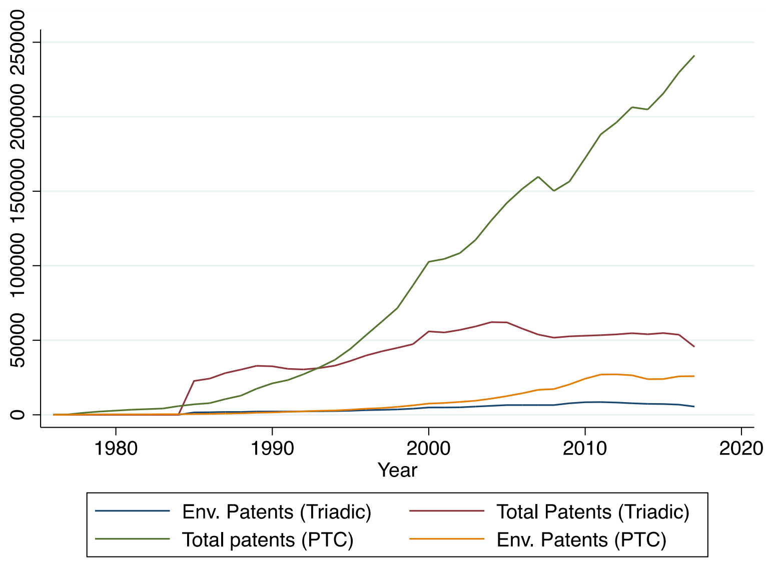

Figure 1. World's trends on environmental and total patents by PTC and triadic families.

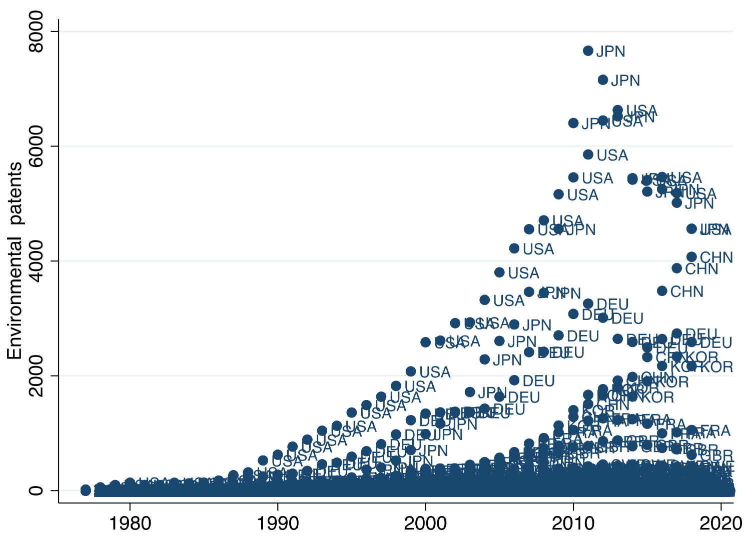

Figure 2. Change in environmental patents over years by country.

Country-level studies mostly use electricity prices retrieved from OECD. The data is separated for industry and household. I take average of both. Additionally, I use crude oil import prices -also available at OECD statistics - to represent the country-level energy prices. Figure 3 compares the trends on electricity price, and tax for household and industry with crude oil prices and environmental patents. All values are averaged over countries for each year. Electricity price for household and crude oil import prices are the ones which corresponds to change in environmental patents over years.

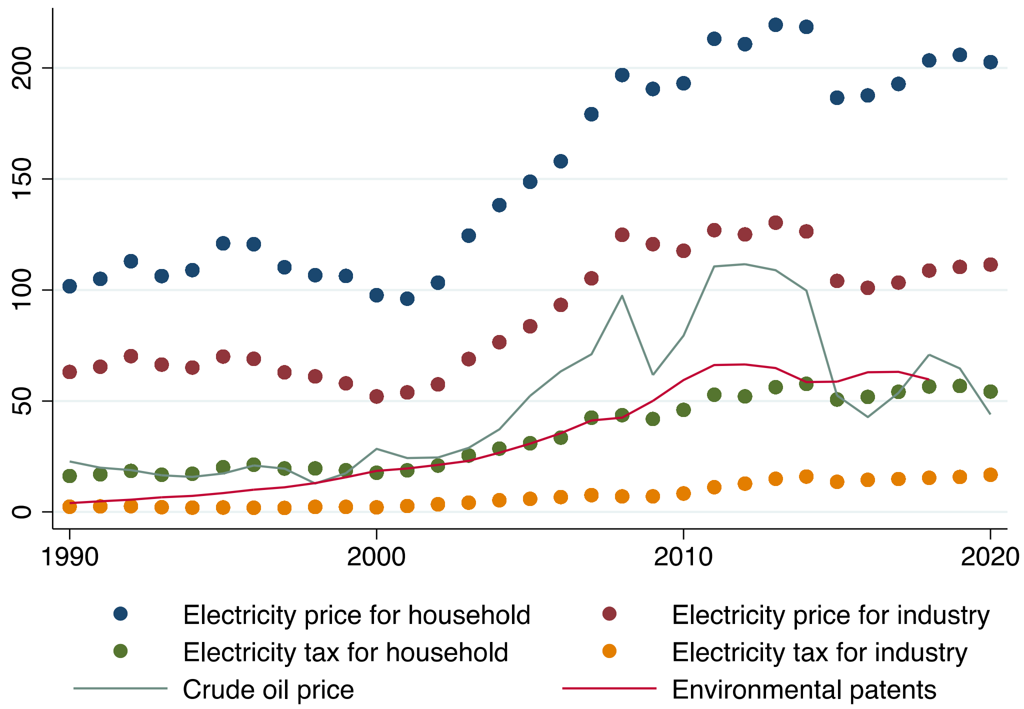

Figure 3. Trends on energy prices and environmental patents over years.

Environmental policy stringency (EPS) is also available at OECD statistics (Kruse et al., 2022). Stringency means the degree to which environmental policies put an explicit or implicit cost on polluting or environmentally harmful behavior. EPS index is available for each policy type that are (i) taxes, trading schemes, feed-in-tariffs (grouped as market EPS) and (ii) standards, R&D subsidies (grouped as non-market EPS). Figure 4 shows the average EPS value for each country within the period. It also presents the difference between market and nonmarket EPS. Japan and Switzerland are among the most stringent countries whereas Brazil and Iceland are the least stringent. I also include dummy variable for Kyoto ratification of countries. Because after signing the Kyoto treaty countries have put more emphasize on environmental policies.

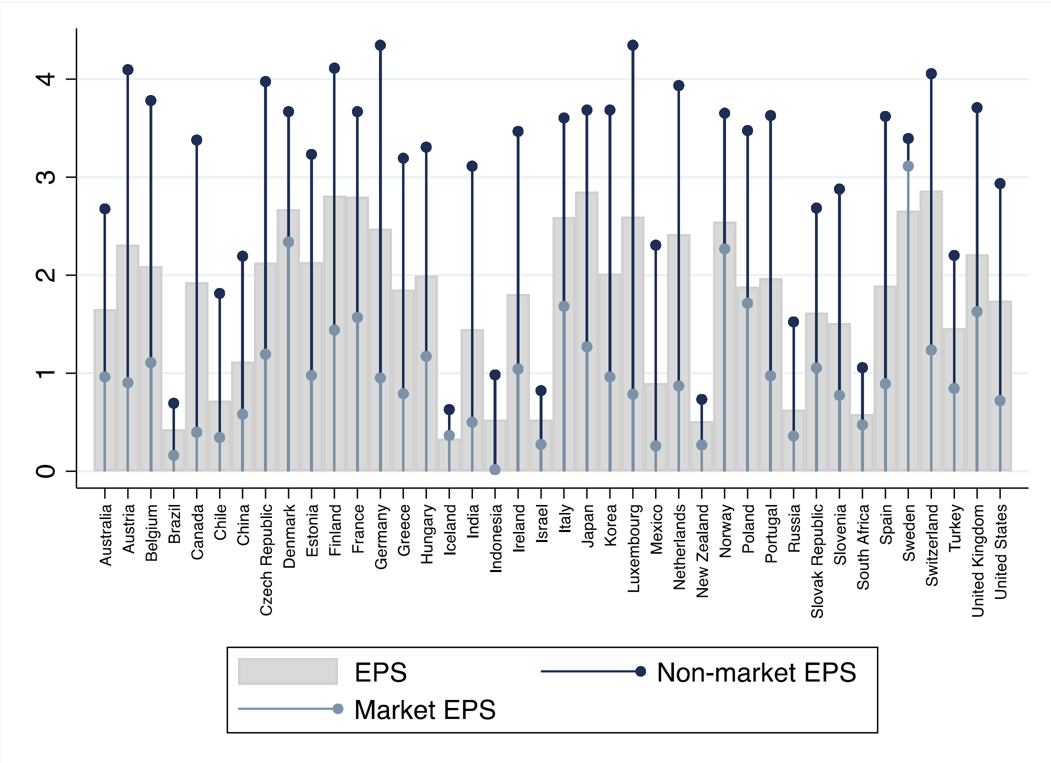

Figure 4. Averaged EPS, market EPS and nonmarket EPS for countries.

Although EPS index contains R&D subsidy stringency, the actual amount of R&D spending is an essential input for the innovative outcome. As endogenous models of climate change (Acemoglu et al 2012) show, R&D is a determinant of the clean innovation. I use R&D spending on renewable energies (also overall energy types for robustness) from

International Energy Agency database. Figure 5 shows the bivariate relationship between R&D spending on renewables vs. environmental patents. They are highly correlated (r=0.8).

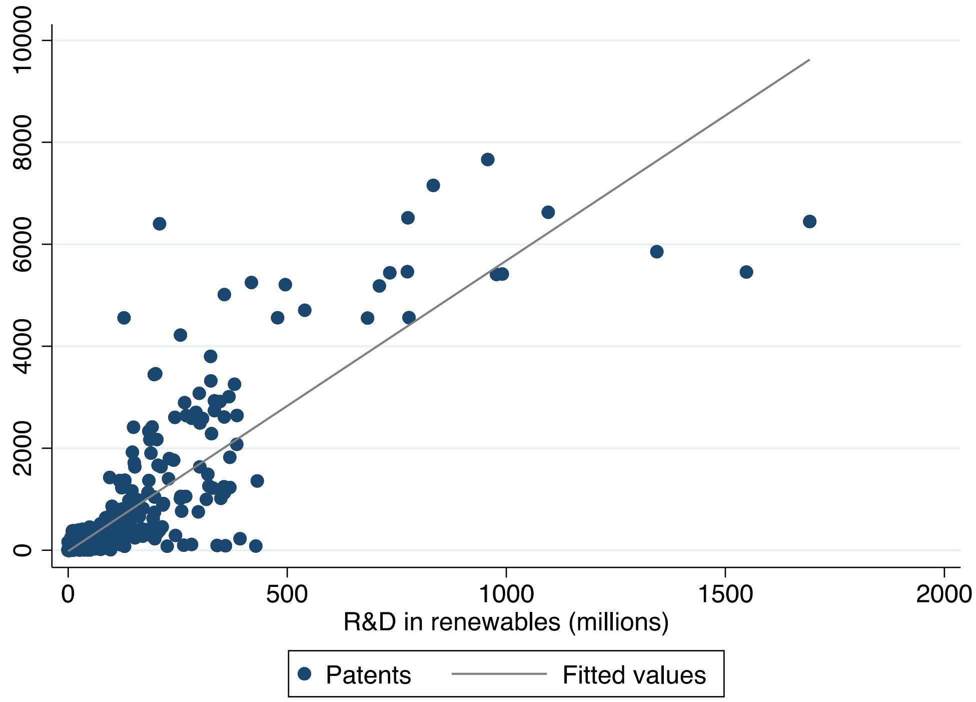

Figure 5. Bivariate relationship between R&D spending in renewables and environmental patents.

Knack and Keefer (1995) introduce the ICRG political indicators while estimating the effect of institutions on economic development. They argue that ICRG indicators are better measurement of institutions based on property rights. ICRG indicators are also broadly used in environment-related studies[6]. I use bureaucratic quality among ICRG indicators that measures the institutional strength to absorb the shock and minimize the revision of policy when governments change. Its range is from zero to four. Countries with higher bureaucratic

[6] Section 2 indicates some literature which uses ICRG indices in studies of institutions and environment.

quality receive higher points. For robustness test, I use political risk rating from ICRG that composes all political indicators and assesses the political stability.

For the control variables, I simply include GDP per capita and Greenhouse Gas (GHG) emission from World Bank's World Development Indicators. Summary statistics and correlation matrix are provided in the Appendix (Tables A2 and A3).

3.2. Econometric Model

Following the Poisson distribution, the main model is as follows:

$$E(EnvPat_{it}|x_{it}, \omega_{it}, \eta_i, \tau_t) = \exp(\alpha x_{it} + \beta \omega_{it} + \eta_i + \tau_t), \tag{1}$$

Where x_{it} are the main regressors of interest including price, policy, and institutions. Next, ω_{it} are the control variables, R&D spending, GDP per capita and GHG emission. Lastly, η_i is a country fixed effect, and τ_t are time dummies. I adopt the log-link formulation due to the count-based nature of the data. Although I apply alternative estimators considering different assumptions on the error term, equation (1) remains the same[7]. The baseline is the Poisson model, where the mean equals the variance. I also consider Negative Binomial, which relaxes this assumption.

Cross-country heterogeneity is an essential feature of panel dataset to deal with. Country fixed effects control for country-specific time-invariant unobserved variables. The prominent literature includes two versions of fixed effects. First, Hausman et al. (1984) introduced the fixed effect Poisson model. However, it requires the strict exogeneity

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[7] Hypotheses 1, 2, and 3 are tested through the Equation 1. For Hypothesis 4, I include the interaction term between policy and institution variables into Equation (1). For Hypothesis 5, I include natural logarithm of overall patents into the Equation (1).

assumption. Second, Blundell et al. (1999) introduced the method “presample mean scaling” (PSM) which relaxes the strict exogeneity assumption. Especially, it is useful when there is a long presample history on the dependent variable to construct the presample average. In my case, environment-friendly patents have a presample data (up to 15 years) that can be used as an initial condition to proxy for unobserved heterogeneity. It also provided the condition that the first moments of the variables must be stationary. Blundell et al. (2002) show that using PSM as fixed-effects more consistent than quasi-differenced GMM and/or traditional fixed effects for dynamic panel data models with weakly endogenous variables.

PSM is calculated as follows:

$$\overline{EnvPat}_i = (\frac{1}{TP}) \sum_{r=0}^{TP-1} EnvPat_{i,0-r} \tag{2}$$

Fixed effects η_i in Equation (1) becomes

$$\eta_i = \gamma ln\overline{EnvPat}_i \tag{3}$$

3.3. Robustness Checks

In addition to comparison of alternative estimators, I provide robustness check using alternative measurements of variables. First, I add more control variables which are used in the literature such as the Kyoto ratification. Second, I replace the patent data signed under PTC with triadic patents. Third, I replace R&D on renewables with R&D on all energy sectors. Fourth, I replace crude oil price with electricity price for households. Fifth, I replace bureaucratic quality with overall political risk rating from ICRG.

3.4. Selection Issues

The coefficient on EPS may be biased because of the reverse causality from innovation to policies. For example, successful innovations in environment-friendly technologies push innovators to lobby for environmental policymaking. Another problem can be measurement errors for the policy variable. Different environmental policies can affect patents in different way. By using an aggregated index for overall policy stringency rather than continuous variables for the actual amount of each type of environmental policies, I likely underestimate the impact of policies on patents. I deal with endogeneity issues by using democratic durability as an instrumental variable for environmental policy stringency.

There is a growing literature about the positive impact of democracies on stringent environmental policies (Congleton, 1992; Fredriksson et al., 2005; Neumayer, 2002; Chang and Berdiev, 2011). In this regard, longer democratic durability is expected to ensure environment-friendly policymaking and long-term implementation compared to younger democracies. For instance, Neumayer (2002) claims that democracies ratify more multilateral agreements, have a national council and relevant information on the environment. Likely, Fredriksson et al. (2005) argue that political competition tends to increase policy stringency as a result of citizens' participation in democracy. I use TENSYS index provided by the World Bank Database on Political Institutions (Beck et al., 2001) to proxy for the time length in which democratic institutions have been consolidated and durable.

I employ control function approach (Blundell and Powell, 2004; Wooldridge, 2015) instead of two-stage least squares (2SLS) because I have nonlinear count data models. When there is a continuous endogenous variable in a nonlinear count data model 2SLS is no longer consistent. Control function also consists of two stages but differently from 2SLS, it includes residuals from the first stage of OLS estimation as a control variable in the second stage of nonlinear count data model.

(4) $$EPS_{it} = \pi TENSYS_{it} + \beta^{o}\omega_{it} + \eta_i^o + \tau_t^o + \epsilon_{it}^o$$

Where ϵ_{it}^o is the residuals and meets the moment condition

(5) $$E(\epsilon_{it}^o | TENSYS_{it}, \omega_{it}, \eta_i^o, \tau_t^o) = 1$$

Therefore, controlling for ϵ_{it}^o in equation (1) sufficiently removes the endogeneity bias.

(6) $$E(EnvPat_{it} | x_{it}, \omega_{it}, \eta_i, \tau_t, \epsilon_{it}^o) = \exp(\alpha x_{it} + \beta\omega_{it} + \eta_i + \tau_t + \rho\epsilon_{it}^o)$$

As a rule-of-thumb, I present the exogeneity test -Durbin-Wu-Hausman test- results for the joint significant of the residuals in equation (6).

4. Results

4.1.Environmental Policies, Institutions and Environmental Patents

Table 1 presents the basic results. Columns 1-3 report Poisson regressions and columns 4-6 report Negative Binomial regressions. Across all the columns of Table 1, the coefficient on EPS lies between 0.255 and 1.273. A coefficient of 0.52 indicates that 10% increase in EPS (e.g., from the mean of 1.8 to 1.98) leads to 5.2% increase in the probability of gaining additional patents (e.g., from the mean of 329 patents to 346). This result is both economically as well as statistically significant.

Table 1. Environmental Policies, Institutional Quality and Environmental Patents

Dependent variable envpat_ptc	(1)	(2)	(3)	(4)	(5)	(6)
Method	Poisson	Poisson	Poisson	Negative Binomial	Negative Binomial	Negative Binomial
EPS	0.560***	0.521***	1.273***	0.255*	0.298**	0.893**
	(0.153)	(0.098)	(0.428)	(0.143)	(0.127)	(0.443)
R&D	0.342***	0.409***	0.452***	0.244***	0.265***	0.280***
	(0.126)	(0.122)	(0.135)	(0.075)	(0.070)	(0.071)
GDPc	-0.389	-0.702**	-0.890**	0.683***	0.486**	0.407
	(0.353)	(0.331)	(0.351)	(0.207)	(0.228)	(0.261)
GHG	0.521***	0.504***	0.460***	0.629***	0.632***	0.605***
	(0.121)	(0.111)	(0.115)	(0.123)	(0.121)	(0.126)
Bureaucratic q.		0.600***	1.339***		0.302*	0.703**
		(0.163)	(0.388)		(0.180)	(0.282)
EPS*Burea.Q.			-0.219*			-0.169
			(0.125)			(0.117)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	687	686	686	687	686	686

Notes. Standard errors are clustered by country. All regressions control for a full set of time dummies. Fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

All columns control for R&D spending in renewable energy, GDP per capita, GHG emission, time dummies and fixed effects[8]. As expected, R&D has a positive and significant association with environmental patents across models. Columns 1 and 4 contain only environmental policy, then I add institutional variable, bureaucratic quality, into columns 2 and 5. Having institutions in the regression slightly decreases the coefficient of EPS from 0.589 to 0.551. And the coefficient on bureaucratic quality is also highly significant, suggesting that the institutional strength to absorb shocks and minimize policy revision

[8] PSM fixed effects are not significant in Poisson while significant in Negative Binomial. When I disregard the fixed effects, the qualitative results are very similar. Fixed effects slightly reduce the marginal effects of EPS and institutions from 0.56 to 0.52 and from 0.76 to 0.60 respectively.

during the government change is essential as much as stringency of environmental policies. Lastly, I include the interaction term between policy and institutions in columns 3 and 6 to measure their joint effect. While the interaction term alone has a positive and significant effect[9], together with EPS and bureaucratic quality it does not necessarily show an impact. In overall, consistent with the bivariate relationships in Figure 6 there is a positive and significant association between EPS, institutions, interaction term and environmental patents.

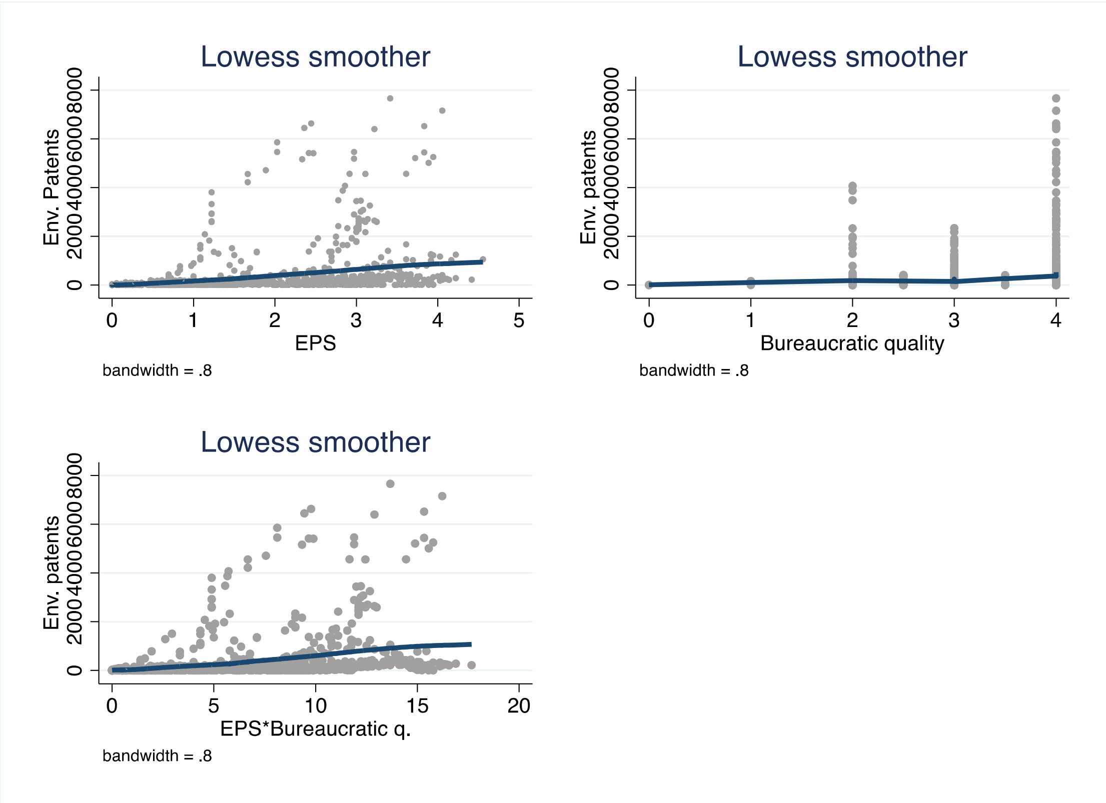

Figure 6. Nonparametric regression on environmental patents and (i) EPS, (ii) bureaucratic quality, and (iii) their joint effect.

[9] Coefficient on the interaction term is significant and positive both in Poisson and Negative Binomial regressions when it is included alone, without EPS and institutions.

4.2.Some Basic Robustness Checks

Table 2. Induced Innovation

Dependent variable envpat_ptc	(1)	(2)	(3)	(4)
Energy price type	Crude oil	Crude oil	Electricity	Electricity
Bureaucratic q.	0.526***	0.931**	0.542***	0.928***
	(0.171)	(0.400)	(0.195)	(0.334)
EPS	0.276***	0.710*	0.416***	0.826**
	(0.097)	(0.413)	(0.110)	(0.366)
Crude oil	0.012	0.011		
	(0.019)	(0.019)		
Electricity			0.002	0.002
			(0.001)	(0.001)
R&D	0.456***	0.458***	0.390***	0.398***
	(0.152)	(0.153)	(0.138)	(0.141)
GDPc	-1.239***	-1.306***	-0.570*	-0.619**
	(0.396)	(0.418)	(0.311)	(0.313)
GHG	0.401***	0.395***	0.528***	0.523***
	(0.116)	(0.118)	(0.117)	(0.119)
EPS*Burea.Q.		-0.117		-0.112
		(0.106)		(0.099)
Fixed Effects	Yes	Yes	Yes	Yes
Observations	625	625	626	626

Notes. Standard errors are clustered by country. Poisson estimator is used in all columns. All regressions control for a full set of time dummies. Fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Energy Prices. I add various measures of energy prices into the baseline specification. At the country-level, crude oil import prices and electricity prices are commonly used measurements. Electricity prices are averaged prices for households and industry. Table 2 presents the results. None of energy prices have an impact on environmental patents. Thus, findings reject the induced innovation hypothesis (Popp, 2022) at the country level. There can be some reasons. For instance, electricity can be generated by clean technologies like the renewables yet at high cost. So, increased electricity prices do not necessarily cause to the use of renewables in electricity generation (in parallel to Johnstone et al (2010)). On the other hand, crude oil import prices are expected to have a direct impact on innovating in environmental patents. However, averaged oil prices do not vary across countries (Figure 7a) rather international oil prices respond to global shocks and vary over years (Figure 7b), so time dummies can absorb its effect. On the other hand, coefficients on EPS and institutions do not change with the inclusion of energy prices.

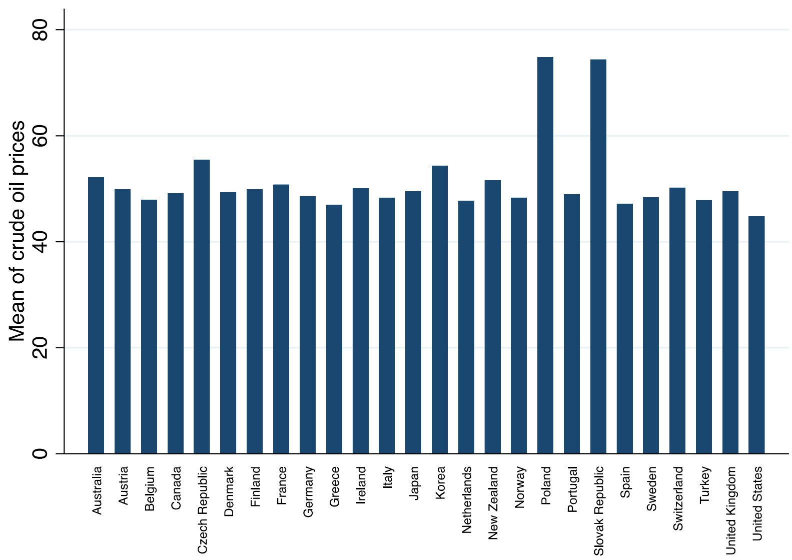

Figure 7a. Crude oil import prices for countries averaged over years.

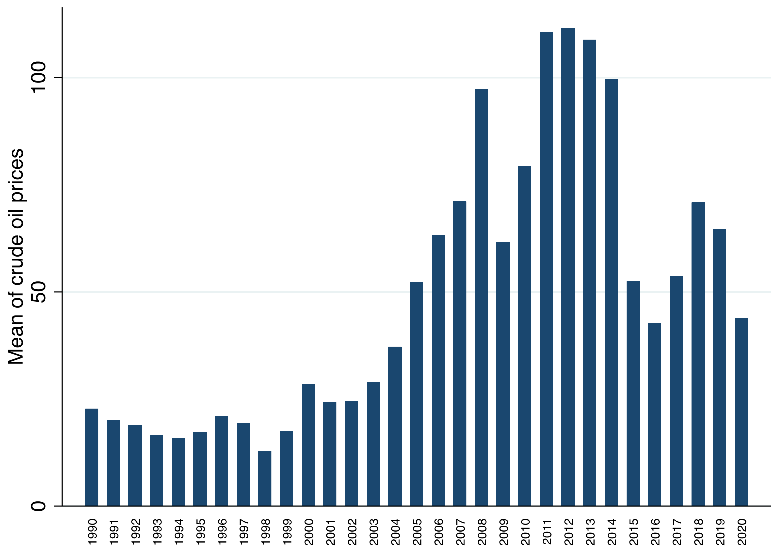

Figure 7b. Countries' averaged crude oil import prices by year.

Kyoto ratification. Signing the Kyoto agreement stimulated the efforts for tackling climate change. Since the correlation between Kyoto dummy and EPS is high (see Table A3 in Appendix), I do not include Kyoto in the baseline estimation. Rather, I present results in Table 3. As expected, Kyoto ratification is significant determinant of countries' innovative activities in environment-friendly technologies. Inclusion of Kyoto dummies does not change the impact of EPS and institutions. It only slightly reduces the magnitudes of coefficients (from 0.52 to 0.40 and from 0.60 to 0.55 respectively).

Table3. Kyoto ratification and Environmental Patents

Dependent variable envpat_ptc	(1)	(2)	(3)	(4)
Bureaucratic q.	0.554***	1.468***	0.505***	0.485***
	(0.152)	(0.384)	(0.167)	(0.171)
EPS	0.397***	1.314***	0.164	0.248**
	(0.101)	(0.445)	(0.101)	(0.106)
Kyoto	0.497*	0.556**	0.570**	0.764**
	(0.289)	(0.278)	(0.272)	(0.358)
R&D	0.403***	0.458***	0.463***	0.384***
	(0.125)	(0.141)	(0.143)	(0.135)
GDPc	-0.446	-0.674*	-0.996**	-0.338
	(0.390)	(0.391)	(0.431)	(0.329)
GHG	0.581***	0.530***	0.463***	0.608***
	(0.149)	(0.150)	(0.139)	(0.149)
EPS*Burea.Q.		-0.273**		
		(0.124)		
Crude oil			-0.011	
			(0.017)	
Electricity				0.000
				(0.002)
Fixed Effects				
Observations	686	686	625	626

Notes. Standard errors are clustered by country. Poisson estimator is used in all columns. All regressions control for a full set of time dummies. Fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Triadic Patents. Alternatively, I can use the environmental patents signed under a specific patent family, called Triadic Patent Family, which represents the patent applications filed under the three largest markets: European, Japanese and US patents offices (EPO, JPO, USPTO).

Table 4. Triadic Patent Family

Dependent variable envpat_tri	**(1)**	**(2)**	**(3)**	**(4)**
EPS	0.744***	0.673***	0.552***	0.975
	(0.230)	(0.191)	(0.156)	(0.635)
Bureaucratic q.	0.620***	0.605***	0.611***	0.991*
	(0.178)	(0.174)	(0.179)	(0.532)
R&D	0.257	0.261	0.289	0.292
	(0.171)	(0.170)	(0.192)	(0.192)
GDPc	-1.100***	-1.017***	-1.315***	-1.406***
	(0.322)	(0.325)	(0.370)	(0.411)
GHG	0.577***	0.602***	0.554***	0.548***
	(0.202)	(0.220)	(0.193)	(0.188)
Kyoto		0.250	0.206	0.195
		(0.226)	(0.249)	(0.244)
Crude oil pri			0.005	0.005
			(0.012)	(0.012)
EPS*Bureau.Q.				-0.115
				(0.158)
Fixed Effects	Yes	Yes	Yes	Yes
Observations	684	684	624	624

Notes. Standard errors are clustered by country. Poisson estimator is used in all columns. All regressions control for a full set of time dummies. Fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Coefficients on EPS and institutions are still consistent with the baseline findings (Table 5). To produce frontier innovations in terms of environment-friendly technologies, countries with more stringent policies and bureaucratic quality perform better. Only R&D and Kyoto lose their significance that is in line with Nesta et al.'s (2014) results for triadic patents. Patent offices represent the economic value and technological quality of inventions

(Squicciarini et al., 2013). So, insignificant effects of R&D and Kyoto may indicate resource misallocation problem (Nesta et al., 2014). Countries, other than frontiers, may focus on technologies which they do not have expertise.

Table 5. R&D spending in all energy sectors

	(1)	**(2)**	**(3)**	**(4)**
Dependent variable	PTC	PTC	Triadic	Triadic
EPS	0.551***	0.319	0.635***	0.590
	(0.107)	(0.380)	(0.223)	(0.604)
Bureaucratic q.	0.549***	0.657*	0.688***	0.913*
	(0.189)	(0.365)	(0.192)	(0.473)
R&D	0.220**	0.340***	0.330***	0.428**
	(0.096)	(0.108)	(0.114)	(0.168)
GDPc	-0.596	-0.871*	-0.957***	-1.134***
	(0.376)	(0.512)	(0.314)	(0.387)
GHG	0.589***	0.488***	0.481**	0.429**
	(0.137)	(0.167)	(0.206)	(0.179)
EPS*Burea.Q.		-0.063		-0.075
		(0.096)		(0.147)
Kyoto		0.707**		0.433
		(0.289)		(0.299)
Crude oili		-0.010		0.009
		(0.020)		(0.014)
Fixed Effects	Yes	Yes	Yes	Yes
Observations	674	629	672	628

Notes. Standard errors are clustered by country. Poisson estimator is used in all columns. All regressions control for a full set of time dummies. Fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

R&D in all energy sectors. R&D spending in renewables is used in the baseline estimations. Alternatively, R&D spending in all energy-related sectors are also available. Table 5 presents the results when I control for public R&D expenditure in all energy sectors. Coefficients on EPS and institutions are in parallel to the previous models. Differently from R&D in renewables, R&D in all energy sectors show a significant and positive impact for triadic patents as well. R&D in renewables may not be enough for frontier technologies whereas

R&D in all energy sectors catch the correct technologies. Kyoto ratification still does not influence triadic patents. Including the interaction term between policy and institutions captures the effect of EPS on environmental patents. Without the interaction term, individual effect of EPS is still visible.

Table 6. Political Risk Rating

	(1)	**(2)**	**(3)**	**(4)**
Dependent variable	PTC	PTC	Triadic	Triadic
EPS	0.541***	-0.337	0.706***	-0.050
	(0.140)	(0.215)	(0.243)	(0.247)
Political risk r.	0.025*	-0.003	0.023	-0.003
	(0.013)	(0.016)	(0.017)	(0.013)
R&D	0.370***	0.453***	0.190	0.277
	(0.129)	(0.142)	(0.174)	(0.188)
GDPc	-0.592*	-0.868**	-1.001***	-1.103***
	(0.341)	(0.395)	(0.353)	(0.345)
GHG	0.527***	0.471***	0.573***	0.562***
	(0.118)	(0.141)	(0.221)	(0.205)
EPS*Pol.r.r.		0.135**		0.163***
		(0.068)		(0.057)
Crude oil		-0.010		0.006
		(0.017)		(0.012)
Kyoto		0.587**		0.242
		(0.276)		(0.258)
Fixed Effects	Yes	Yes	Yes	Yes
Observations	686	625	684	624

Notes. Standard errors are clustered by country. Poisson estimator is used in all columns. All regressions control for a full set of time dummies. Fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Political risk rating. In addition to the bureaucratic quality, ICRG provides a comprehensive index called political risk rating (PRR). In Table 6, I replace the proxy for institutions with PRR. First, coefficients on EPS, renewables' R&D, crude oil prices and Kyoto are like the previous models. Interesting results of Table 6 are follows. Individual effect of PRR is not consistent across models. The robust impact of the bureaucratic quality index can be compensated by other components of PRR. On the other hand, the joint effects of environmental policies and political risk rating is significant and positive for both all patents and triadic patents. While bureaucratic quality is individually a determinant of environmental patents, environmental policies need less risky political environment to increase its impact.

Table 7. Market vs. Nonmarket environmental policies and Patents

Dependent variable envpat_ptc	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
EPS type	Market	Market	Market	NonMarket	NonMarket	NonMarket
Market EPS	0.298*	0.142	0.068			
	(0.156)	(0.105)	(0.598)			
Nonm. EPS				0.182**	-0.042	0.862**
				(0.083)	(0.067)	(0.359)
Bureaucratic q.	0.814***	0.536***	0.502	0.669**	0.494***	1.681***
	(0.299)	(0.171)	(0.316)	(0.325)	(0.163)	(0.367)
R&D	0.578***	0.497***	0.497***	0.634***	0.523***	0.512***
	(0.098)	(0.123)	(0.123)	(0.103)	(0.122)	(0.119)
GDPc	-0.945**	-1.076**	-1.071**	-0.887*	-1.079**	-1.160**
	(0.450)	(0.455)	(0.463)	(0.463)	(0.455)	(0.457)
GHG	0.348***	0.458***	0.460***	0.267***	0.396***	0.380***
	(0.120)	(0.148)	(0.151)	(0.076)	(0.133)	(0.125)
Crude oil		-0.011	-0.011		-0.013	-0.018
		(0.016)	(0.017)		(0.018)	(0.017)
Kyoto		0.656***	0.657***		0.738***	0.746***
		(0.247)	(0.251)		(0.262)	(0.262)
M.EPS*Bur.Q.			0.020			
			(0.161)			
NonM.EPS*Bur.Q.						-0.236***
						(0.087)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	686	625	625	686	625	625

Notes. Standard errors are clustered by country. Poisson estimator is used in all columns. All regressions control for a full set of time dummies. Fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

Market vs. Non-market EPS. Lastly, I compare effects of environmental policies as distinguished by market vs. nonmarket policies. Both market and nonmarket EPS have a positive and significant effects on environmental patents while the magnitude of the coefficient on market EPS is higher than nonmarket eps' (0.298 vs 0.182). Their significance disappears when Kyoto dummy is included in the regression. Bureaucratic quality is still significant determinant of innovation while its joint effects with policies do not necessarily cause to better performance in environmental patents.

Overall, these results provide robust results for positive effect of policies and institutions on innovation.

4.3. *Endogeneity of environmental policy stringency*

Table 8. Environmental Policies, Institutional Quality and Environment-friendly Patents – Controlling for Endogeneity

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Dependent vr.	Env.patent	EPS	Env.patent	Env.patent	EPS	Env.patent	Env.patent	Env.patent	Env.patent
Estimation method	Poisson	OLS (1st stage)	Poisson (Control function)	Poisson	OLS (1st stage)	Poisson (Control function)	Poisson (Control function)	Poisson (Control function)	Poisson (Control function)
Sample	All	All	All	All	All	All	All	High str.	Low str.
EPS	0.558***		1.250***	0.521***		1.229***	1.297***	1.234***	0.032
	(0.098)		(0.150)	(0.098)		(0.205)	(0.389)	(0.264)	(0.242)
Bureaucratic q.	0.758***		0.405*	0.600***		0.439**	0.504	0.517***	0.356*
	(0.234)		(0.218)	(0.163)		(0.179)	(0.399)	(0.181)	(0.200)
TENSYS		0.074***			0.073***				
		(0.005)			(0.005)				
EPS*Burea.Q.							-0.019		
							(0.094)		
Fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Exogeneity test p. value			0.000			0.000	0.000	0.000	0.367
Observations	686	683	658	686	683	658	658	395	263

Notes: Standard errors are clustered by country. All columns control for ln(GDPc), ln(GHG), R&D, and time dummies. TENSYS is the time length for democratic institutions. Fixed effects controls using the Blundell, Griffith, and Van Reenen (1999) presample mean scaling estimator. Exogeneity test at the second stage is Durbin-Wu-Hausman test for the coefficient on residuals from the first stage. *** Significant at the 1 percent level. ** Significant at the 5 percent level. * Significant at the 10 percent level.

In this section, I consider an instrumental variable strategy to tackle possible endogeneity of environmental policies. I am concerned that the positive correlation between environmental policies and innovation is stemmed from selection. As discussed in Section 3, democratic durability is expected to increase the stringency of environmental policies.

Table 8 presents results for both first stage and second stage regressions. The first column assumes exogeneity of policy variable and does not control for fixed effects. Column 2 presents the first stage where EPS is regressed on TENSYS and all other controls. As expected, the instrument – democratic durability – is positive and highly significant. One year longer consolidated democracy results in 7% more stringent environmental policies (from mean of 1.78 to 1.9). Column 3 presents the second stage where the control function method is used. Coefficient on EPS is still significant, and its magnitude is doubled. OLS is biased toward zero that means an attenuation bias due to measurement error. This result suggests that the impact of EPS is underestimated when it is assumed as exogenous.

Columns 4-6 repeat the models of the first three columns with fixed effects. All models have consistent results. Inclusion of fixed effects only cause to a slight decrease in coefficient on EPS. This suggests that fixed effects are not responsible for a considerable part of the endogeneity. Next, Column 7 includes the interaction term between EPS and bureaucratic quality and repeat the model in Column 3 of Table 1. The interaction has no effect on patents even when EPS is treated as endogenous. Therefore, significancy of the interaction term at 10 percent level in Column 3 of Table 1 is a biased result. Last two columns of Table 8 divide the sample into countries with high and low stringency of environmental policies by the mean value. While the EPS is highly and economically significant in countries with high stringent policies, its affect disappears in countries with low stringent policies (and the instrument is significant in both first stages). This suggests that countries should exceed a threshold to benefit from environmental policies in terms of innovative outcome.

5. Conclusions

Given the importance of innovation in tackling climate change, it is important to understand institutional determinants of environment-friendly innovation at the country level. This paper attempts to estimate the relationship between environmental policies, political institutions, and environmental patents.

In support of existing literature, more stringent policies boost innovation. The evidence from democratic durability as an instrument suggest that this result stem from endogenous selection. In addition to policies, scholars remind the need for institutions while implementing green industrial policies, so bureaucratic quality facilitates innovation. Their positive effects are robust to controlling for R&D spending. Alternative models are also consistent with these baseline findings. Moreover, Kyoto ratification stimulated countries' efforts to environment-friendly innovation, as expected. However, contrary to the induced innovation hypothesis, energy prices do not induce innovation in this study. Insignificant impacts of crude oil import prices and electricity prices could derive from their relatively small roles in carbon pricing. Studies who support the induced innovation hypothesis mostly do firm-level analysis and use more direct measurement of carbon taxes.

This study has implications for countries. While environmental policies are required to increase innovation in green technologies, the institutional environment has also essential role for successful implementation of these policies. Bureaucratic quality demonstrates a country's ability to adopt to government changes by minimizing policy revision. Indeed, environmental policies need long-term commitment to reach an effective outcome. However, especially democratic governances are subject to change in the short-term. Therefore, how a country absorbs shocks during the change will determine the effectiveness of environmental policies and bring in green innovation.

This study also has some limitations. It uses the stringency of environmental policies rather than specific policy indices such as feed-in-tariff, carbon taxes, portfolio standards, etc. It would be helpful for governments to observe the impacts of specific policy types while determining the next environmental policy targets. Furthermore, despite the estimations with alternative variables, models can still suffer from omitted variable bias which affect the interpretation of causality from policies, and institutions to innovation. Yet, I believe that the results are unsusceptible to such bias because pre-sample mean correctly captures any potential country specific and time-invariant characteristics. Nevertheless, further research can be done in more comprehensive way, for instance, with the inclusion of path-dependency in green innovation.

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Appendix

Table A1. List of Countries.

Australia	Denmark	Hungary	Mexico	Slovak Republic	United States
Austria	Estonia	Ireland	Netherlands	Spain	
Belgium	Finland	Italy	New Zealand	Sweden	
Brazil	France	Japan	Norway	Switzerland	
Canada	Germany	Korea	Poland	Turkey	
Czech Republic	Greece	Luxembourg	Portugal	United Kingdom	

Table A2. Summary statistics.

Variables	Observations	Mean	Standard deviation	Min	Max
Env. patents (PTS)	1,160	329.55	914.36	0	7662.5
Env. patents (Triadic)	1,150	128.52	386.93	0	3536.4
EPS	1,240	1.78	1.19	0	4.9
Non-market EPS	1,240	2.96	2.006	0	6
Market EPS	1,240	0.98	0.806	0	4.2
Bureaucratic Quality	1,213	3.33	0.79	0	4
Political Risk Rating	1,212	77.12	10.49	35	97
crude oil import price	756	50.27	31.71	11.7	117.8
electricity price	896	123.79	53.28	17.8	285.16
kyoto dummy	1,240	0.58	0.49	0	1
(ln) R&D in renewables	741	17.17	1.825	9.1	21.7
(ln) R&D in all energy sectors	730	18.98	1.77	14.6	23.2
(ln) GDP per capita	1,210	9.91	1.017	6.3	11.63
(ln) GHG emission	1,200	12.19	1.65	7.9	16.36

Table A3. Correlation matrix.

	Env. patents	EPS	Bureaucratic q.	crude oil	kyoto	R&D ren.	GDPc	GHG
Env. patents	1.0000							
EPs	0.232	1.0000						
Bureaucratic q.	0.165	0.012	1.0000					
crude oil	0.209	0.666	-0.067	1.0000				
kyoto	0.031	0.713	-0.0930	0.688	1.0000			
R&D ren.	0.598	0.515	0.218	0.309	0.198	1.000		
GDPc	0.166	0.320	0.754	0.1310	0.137	0.425	1.000	
GHG	0.617	-0.042	-0.026	-0.029	-0.169	0.611	-0.074	1.000