Global Patterns of Renewable Energy Innovation, 1990-2009*

Patrick Bayer† Lindsay Dolan‡ Johannes Urpelainen§

6 March 2013

Abstract

Cost-effective approaches to mitigating climate change depend on advances in clean energy technologies, such as solar and wind power. Given increased technology innovation in developing countries, led by China, we focus our attention on global patterns of renewable energy innovation. Utilizing highly valuable international patents as our indicator of innovation, we examine the economic and political determinants of energy innovation in 74 countries across the world, 1990-2009. We find that high oil prices and domestic renewable electricity generation capacity both increase innovation. There is no effect for corruption, but our findings suggest that democratic institutions may contribute to innovation. The main implication of our work for policymakers is that increasing renewable electricity capacity in developing countries could significantly contribute to global innovation in renewable energy.

Keywords: environmental policy, clean technology, innovation, renewable energy, patents

*We thank Andrew Cheon for helpful comments on a previous draft.

†Corresponding author. Department of Political Science, University of Mannheim, D7, 27, 68131 Mannheim, Germany. Phone: + 49 621 181 2418. Fax: + 49 621 181 3699. Email: pbayer@mail.uni-mannheim.de

‡Department of Political Science, Columbia University, New York City, USA.

§Department of Political Science, Columbia University, New York City, USA.

1 Introduction

The world's reliance on fossil fuels for modern energy services is the primary cause of climate change and many other environmental ills. Abating environmental pollution in the energy sector demands the deployment of cleaner energy, especially advanced renewable energy technologies (Neuhoff, 2005). However, widespread adoption of renewable energy technologies requires innovations that enhance the performance and reduce the cost of key energy forms, such as solar and wind (Cheon and Urpelainen, 2012).

Motivated by the current need to develop new renewable energy technologies, this article examines the determinants of renewable energy innovation on a global scale, 1990-2009. While industrialized countries have historically been the primary sources of renewable technology innovation, in recent years many developing countries, including China and India, have begun to play an important role as innovators in this field. This trend is readily seen in Figure 1, which shows the cumulative count of renewable energy patent applications filed under the 1976 Patent Cooperation Treaty (PCT) in four major developing countries. While China clearly tops the list of total renewable energy patents, high compound annual growth rates in India (+50.3%), Brazil (+33.2%), and South Africa (+22.3%) show that the global landscape of renewable energy innovation is being changed by other emerging economies as well.

[Figure 1 about here.]

Given this pattern, we conduct a global analysis of patenting. Following convention, we measure private innovation by a count of highly valuable international patents (Archibugi and Pianta, 1996; Basberg, 1987; Johnstone et al., 2010). Estimating negative binomial count models for international renewable energy patents, we examine how different economic and political factors shape innovative activity in 74 countries during the time period under investigation. Each country in the dataset produces at least one international renewable energy patent during the period under investigation, as all completely inactive countries are excluded from the sample when we include country fixed effects.

We find that of the factors under investigation, domestic renewable electricity generation capacity and oil prices have strong positive effects on patenting activity. A one standard deviation increase in renewable electricity capacity increases the predicated ratio of expected renewable patents counts by 50%, while an identical increase in oil prices increases this ratio in expectation by 13%. We also find that democratic institutions have a sizeable effect on patent innovation, but this finding is sensitive to the specification of our econometric models; hence, we caution against overstating the influence of political institutions. Finally, corruption does not seem to affect the number of patent applications.

Our main results continue to hold when we interact our key explanatory variables with OECD membership, but the effects for renewable electricity generation and oil prices are smaller for OECD countries compared to non-OECD countries. This implies that the increase in patent applications is less pronounced for OECD countries than for non-OECD when renewable electricity generation and oil prices rise. When we analyze our data separately for wind, solar, and hydroelectricity patents, we see some noticeable differences. Only for solar patents do both renewable electricity generation capacity and oil prices seem to matter. For hydroelectricity patents, in contrast, the effect of oil prices becomes negligible, while for wind patents renewable electricity capacity does not seem to affect the filing of renewable energy patents.

From a policy perspective, the overall finding that renewable electricity capacity matters is welcome. As the rapid growth of renewable electricity generation in developing countries continues, their innovative capacities may also be expected to improve. Investments in generation capacity not only abate carbon emissions, but also create technological innovations that further enhance the competitiveness of renewable energy.

2 Renewable Energy Innovation: A Global Overview

While renewable energy innovation has historically concentrated in industrialized countries, it increasingly occurs in powerful emerging economies. Lanjouw and Mody (1996) observed that Brazil and India initially led environmental innovations among developing countries, while East Asian countries tended to innovate in other industries. More recently, Dechezleprêtre et al. (2011) track climate change mitigation technology leaders and find that China, South Korea, Russia, and Brazil rank among the top global inventors. While these economies may be emerging as innovative actors in environmental technology, they do not yet export their technologies to either developed or other developing countries on any significant scale. Both studies find that the inventions of these countries tend to be of relatively minor economic value and primarily aim to adapt technologies from leaders like Japan, the United States, and Germany to the developing world.

Despite these present limitations on the inventions of developing countries, recent trends suggest that environmental innovation from developing countries is becoming more plausible. The trends discussed in the introduction suggest that, at least in the case of emerging economies, valuable renewable energy innovations are no longer limited to OECD countries. Accordingly, we conduct a global analysis of renewable energy innovation.

To illustrate, consider the fact that China filed almost 500 PCT applications during the 1990-2009 period, with most of these being recent. The United States, Japan, and Germany filed 3,918, 2,345, and 2,195 patents under the PCT during the same time period, respectively. Indeed, China holds more PCT patents than large OECD countries, such as Canada (285 patents), Italy (359), and Australia (379), and ranks ninth worldwide.

We examine *renewable energy innovation*, defined as processes by which new energy technologies are invented and technically improved for commercial use. Following convention, we measure technology innovation by patent counts. The usual objection raised to this measure of innovation is that patents may be awarded to significant and minor inventions alike (Archibugi and Pianta, 1996; Basberg, 1987). Since we use highly valuable international patents, we can overcome this limitation.

If we accept patents as a meaningful, if perhaps intermediate, measure of innovation, the question arises why some countries are more innovative than others. At the heart of the economic literature on innovation is the theory of "induced innovation," which posits that a change in relative price spurs innovation. Applied to environmental innovation, this suggests that an increase in the price of oil should result in an increase in technological advancement. Previous empirical work has attributed 25-50% of the improvement in the energy efficiency of home appliances to increases in energy prices (Newell et al., 1999; Popp, 2001). Cheon and Urpelainen

(2012) also find that high oil prices have promoted renewable energy innovation in those OECD countries that already produce renewable energy. As Dechezleprêtre et al. (2011) note, however, oil prices and patents aligned only until 1990, after which patents continued to increase despite stable oil prices. This suggests a space for government policy, innovative capacity, or other factors to account for renewable energy innovation.

One permutation on induced innovation is the Porter hypothesis, which identifies regulation as the cause of innovation (Porter and Linde, 1995). Support for the hypothesis in the context of environmental innovation comes from Lanjouw and Mody (1996), who have traced a strong association between pollution abatement expenditures and environmental patents in the 1970s and 1980s, and from Lee et al. (2010), who show that US automotive firms facing stricter emission standards generated more patents. Other empirical research has highlighted some gaps in research on regulation. Jaffe and Palmer (1997) find that while increased compliance expenditures within an industry result in more R&D, they do not necessarily produce more patents.

The literature also emphasizes domestic demand for technologies. Cheon and Urpelainen (2012) show that OECD countries with a lot of renewable electricity generation capacity also produce more international patents, while Lewis and Wiser (2007) find that competitive wind turbine manufacturers have emerged in countries that have used policies to create a large domestic market for their technologies. In the general case of environmental innovation, Huber (2008) refers to such countries as "pioneer countries."

2.1 Economic Hypotheses

We begin first by testing the theory of induced innovation. We do so by looking at oil prices (Newell et al., 1999; Popp, 2001). Oil is the central energy commodity traded in markets, and oil prices have historically exhibited a high correlation with other energy prices (Villar and Joutz, 2006). Since oil is used in virtually every sector of the energy economy, including electricity generation, high oil prices indicate general energy scarcity. Such scarcity creates demand for forms of energy like solar and wind power that are not subject to variable fuel costs.

Hypothesis 1 (oil prices and renewable technology innovation). *High oil prices have a positive effect* *on renewable energy innovation.*

We expect that when oil prices are high, more innovators will be incentivized to research and commercialize renewable energy technology.

Next, we examine the importance of the domestic technology market for innovation. We expect that countries in which a domestic market for renewable energy exists will be home to more innovation in the future. To measure this, we identify renewable electricity capacity as a variable that captures a country's home market potential. Previous research on renewable energy innovation and commercialization suggests the existence of a strong home market bias (Lewis and Wiser, 2007; Huber, 2008), meaning that countries with a large market for renewable electricity generation are likely to host innovative technology supplies.

Hypothesis 2 (renewable electricity generation and renewable technology innovation). *Increasing renewable electricity generation capacity has a positive effect on renewable energy innovation.*

We predict that countries that have already acquired a strong capacity for renewable electricity generation have greater degrees of physical and human capital for contributing to more innovations in the future. More firms are likely working on and competing for these technologies, which will increase the number of patents resulting from renewable energy innovation.

2.2 Political Hypotheses

Political factors also contribute to a productive investment environment for environmental innovation. Markets are successful when they are backed by political configurations that protect property rights, provide public goods, and defend security. Among developing countries there exists a greater diversity of institutional arrangements than among OECD countries alone. Consequently, in addition to the economic hypotheses outlined above, we also include political differences as potential determinants of environmental innovation.

We first consider whether democratic regimes create more inviting contexts for investment in researching new technologies. Democratic governments are more likely than autocracies to provide collective goods because use of taxpayer money binds the state to reinvesting that revenue in works that benefit the public. While some autocrats may also invest in projects to benefit the people, they are far more likely to use extracted wealth for individual gain (Wintrobe, 1998; Olson, 2000; Bueno de Mesquita et al., 2003). Roads, infrastructure, electricity, security, and education, among other public goods, make democracies an attractive environment for innovation because companies can employ educated workers and operate efficiently on long-term innovation projects with a reasonable assurance of stability.

Moreover, there is empirical evidence that democratic countries more frequently enact environmental policies. A clean environment is a public good, and empirical evidence suggests that democratic governments, both OECD and non-OECD, depend on the provision of environmental public goods for political support (Neumayer, 2002; Li and Reuveny, 2006). Renewable energy does not generate as much environmental pollution as fossil fuels do, so one would expect democratic governments to show stronger interest in renewable sources than autocratic governments show.

Finally, when democratic governments must use public money to finance state projects, they must protect property rights. Property rights are a critical characteristic of democracies because they legitimize government borrowing from the public precisely by limiting that power (North and Weingast, 1989). These political and economic liberties should attract innovators to research in democracies, in which governments have credibly committed to letting economic actors reap the rewards of their efforts.

Hypothesis 3 (democracy and renewable technology innovation). *Democratic political institutions have a positive effect on renewable energy innovation.*

Next, we expect that corrupt regimes, be they democratic or not, discourage investment and innovation. Whereas we hypothesize that a democratic structure theoretically stabilizes an economic climate, corruption has the opposite effect of producing distortions in an economy (Mauro, 1995; Rose-Ackerman, 1999). Firms are less likely to invest in countries with reputations for corruption because of the increased transaction costs in terms of money (e.g. bribes) and time (e.g. processing delays). These distortions are exaggerated with respect to innovation. Since invention frequently occurs among outsiders to mainstream production and research, the exclusion of these actors from the privileged elite will compromise the ability to innovate (Shleifer and Vishny, 1993). Corruption may prove particularly problematic in the case of renewable energy, because opponents of clean energy technologies, such as owners of coal plants, may also bribe corrupt officials to raise regulatory barriers to new innovation.

Hypothesis 4 (corruption and renewable technology innovation). *Corruption has a negative effect on renewable energy innovation.*

3 Research Design

To test our hypotheses, we collected data on renewable energy patents. The data come from the OECD database *StatExtracts* and capture filings of renewable energy patents under the the PCT, 1990-2009.[1] We exclude years before 1990 because there was virtually no innovation in most countries until that time. As our unit of analysis, we use country-years. We initially have a perfectly balanced panel with 190 countries, but 63 of them do not produce any patents during the time period investigated, and so the inclusion of fixed effects results in their removal. Within the remaining data, we lose another 53 countries and some years due to data limitations for the explanatory variables, leaving us with 74 countries in our dataset. To account for the count distribution of the dependent variable, we estimate negative binomial models.

3.1 Dependent Variable

The dependent variable is the count of patent filings with the PCT.[2] This international treaty to protect intellectual property was negotiated in 1970 and the first filings were received in 1978. International patent applications are highly standardized procedures. These procedures involve examining patentability, searching for already existing and relevant patents, and preparing documents for national registration. Since this demanding process requires several years, official translations of documents, and registration fees, only valuable innovations are registered under the PCT. Therefore, PCT filings predominantly capture valuable innovations with high commercial value. Since these high-value patents are more likely than low-value patents to be used for

[1] See `http://stats.oecd.org/Index.aspx?DatasetCode=PATS_IPC`. Accessed on April 18, 2012.
[2] See `http://www.wipo.int/pct/en/texts/articles/atoc.htm`. Accessed on September 16, 2012.

commercially successful products, our patent count measure is strongly associated with product innovation. This connection between international patent filings and major technological innovation has been established in relevant literature (e.g., Johnstone et al., 2010; Archibugi and Pianta, 1996). Additionally, centralized data collection under the PCT makes our dependent variable a reliable empirical measure by avoiding missing data and inconsistent coding.

3.2 Independent Variables

To test both economic and political determinants of energy innovation, we use four independent variables in our statistical model.[3] First, we hypothesized that higher oil prices induce faster growth in renewable energy innovation. We expect a positive relationship between oil prices, measured in constant 2010 US$ per barrel, and renewable energy innovation. The oil price data are from British Petroleum's 2010 *Statistical Review of World Energy*. Since it has an approximately normal distribution, we do not logarithmize it.

Second, countries with high levels of installed renewable electricity capacity should innovate more. We measure installed renewable electricity generation capacity in million kW. Due to the non-normal distribution, we logarithmize the measure. Since hydroelectricity generation is a mature technology, we exclude it. The data are from the United States Energy Information Administration.

Third, we test whether democratic institutions are conducive to renewable energy innovation. To measure democratic institutions, we use a binary indicator if elections in a country are free or not (Cheibub et al., 2010).

Fourth, we test a hypothesis that establishes a negative relationship between renewable energy innovation and corruption. We measure corruption using data from the *International Country Risk Guide*, where higher levels denote more corruption.

3.3 Control Variables

To avoid omitted variable bias, we add control variables to some of our models.[4] All data for our control variables are from the *World Development Indicators* and lagged by one year to avoid

[3] Histograms to illustrate the distributions of our main variables can be found in the supplementary appendix.
[4] Again, the distributions for all control variables can be found in the supplementary appendix.

simultaneity bias.

Next, we include logarithmized GDP. Large countries have more potential for innovation by virtue of their size, and so we expect a positive effect on patent counts.

We also include net inflows of foreign direct investments as percent of GDP. Since we focus on international patents, investment patterns may prove important. Countries that attract a lot of foreign direct investment host multinational companies that are potentially interested in international patents. For similar reasons, we add the sum of imports and exports as percent of GDP.

Our most comprehensive model also controls for urban population as share of total population and urban air pollution, measured as concentrations of suspended particulate matter (PM10). These factors are included to account for the possibility that countries with large urban populations or large urban air pollution file more renewable patent applications.

Finally, all our models contain a binary indicator for OECD membership, a linear time trend, and a set of regional control variables for Africa, Asia, and the Americas. We use regional dummies for Europe and Oceania as the baseline category to ensure estimation stability. The inclusion of the OECD indicator and regional dummies is possible, because the country fixed effects in a count model are used to account for dispersion heterogeneity.

In Tables 2 and 1 we present the summary statistics and a correlation matrix. Except for the rather high and statistically significant correlations between OECD membership and renewable electricity capacity ($r = 0.663$) and corruption ($r = -0.596$), the correlations are not so large as to raise concerns of multicollinearity.

[Table 1 about here.]

4 Results

The results of our quantitative analysis support two of the hypotheses, as oil prices and renewable electricity generation capacity increase patenting activity. We also find some evidence that democratic countries produce more renewable energy patents, but this finding is not particularly robust. Following the presentation of the main findings, we analyze differences between OECD

Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1) Renewable patents count	1.000										
(2) Oil prices (lagged)	0.245***	1.000									
(3) Renew electricity capacity (lagged, logged)	0.343***	0.172***	1.000								
(4) Democracy (lagged)	0.095***	0.022	0.355***	1.000							
(5) Corruption (lagged)	-0.086**	0.234***	-0.332***	-0.358***	1.000						
(6) OECD membership (lagged)	0.229***	-0.013	0.663***	0.434***	-0.596***	1.000					
(7) GDP (lagged, logged)	0.401***	0.030	0.662***	0.119***	-0.204***	0.484***	1.000				
(8) FDI (pct GDP, lagged)	-0.028	0.036	-0.010	0.057*	-0.106***	0.119***	-0.111***	1.000			
(9) Sum of imports and exports (pct GDP, lagged)	-0.098***	0.184***	-0.188***	-0.071*	-0.066*	0.011	-0.332***	0.426***	1.000		
(10) Urban population (pct total, lagged)	0.123***	0.061*	0.207***	0.245***	-0.381***	0.408***	0.297***	0.121***	0.121***	1.000	
(11) Urban air pollution (PM10, lagged)	-0.132***	-0.176***	-0.321***	-0.354***	0.343***	-0.438***	-0.088**	-0.103***	-0.208***	-0.412***	1.000

Table 1: Correlation matrix for renewable energy innovation. The numbers based on the model that includes all the control variables discussed above.

and non-OECD countries. Finally, we consider differences across renewable energy industries.

4.1 Main Findings

Table 3 presents the main findings. Model (1) includes only the OECD membership indicator as a control variable. Models (2) and (3) exclude years before 1995 and after 2007, respectively. Models (4) and (5) include more control variables. Using the Akaike Information Criterion (AIC) (Akaike, 1974) to assess model fit, all our five models show good model fit relative to model (3), which minimizes the AIC. Following Burnham and Anderson (2004: 271), we also verified that the differences between the AIC values between model (3) and the others are small, indicating that our different models are similar in terms of model fit.

As to our main explanatory variables, the effects of oil prices and renewable electricity capacity are positive and statistically significant across the models. The effect of democracy is robust except for model (5), and corruption does not have a statistically significant effect in any of the models.

[Table 2 about here.]

Of the control variables, GDP has a positive effect in one of two models. Trade and urban air pollution unexpectedly have negative effects on patenting. The negative trade effect could be driven by the importance of large domestic markets and even tariff protection for innovation, while urban air pollution may have a negative correlation with innovation activity because pollution levels tend to be higher in countries that do not have access to advanced environmental technologies.

We next simulated substantive effects for changes from the mean to one standard deviation above the mean for our independent variables. Since our democracy variable is a binary indicator, we calculated substantive effects for changes from an autocratic to a democratic regime type. Figure 2 below then plots these substantive effects separately for the hypothesized economic and political determinants. All simulations are based on model (4), and confidence bounds come from 1,000 draws from a multivariate normal distribution (King et al., 2000). All covariates are kept at their means, while we keep binary variables and fixed-effects at their median values.

[Figure 2 about here.]

In addition to highlighting the irrelevance of corruption, the substantive effects plots provide three interesting insights. First, while oil prices have a positive effect, it is relatively small for any given country. An increase of one standard deviation (US$ 22) increases patenting activity by 14%. Overall, though, the effect may be large because it applies to *all* countries at the same time. Second, renewable electricity generation capacity has a positive effect on innovation. An increase of one standard deviation in the logarithmic transformation raises the number of patents by 53%. Given large differences across countries in generation capacity, this variable explains a lot of cross-national variation. Finally, the expected effect of democracy is large. On average, democracies produce 2.28 times as many patents as autocracies. However, it is important not to overstate this finding, given that it disappears if we include more controls, as in model (5) of Table 3.

4.2 Comparing Industrialized and Developing Countries

While we mainly focus on global patterns, we also evaluate differences across OECD and non-OECD countries. We do so by successively interacting our OECD indicator with each of the four key explanatory variables. The results are reported in Table 4. The table shows the following patterns:

- Oil prices have larger positive effects on innovation in non-OECD than in OECD countries.
- Renewable electricity capacity has a larger positive effect on innovation in non-OECD than in OECD countries.
- The effect of democracy does not differ across OECD and non-OECD.
- The effect of corruption on innovation in OECD countries may even be positive.

The strong effects of oil prices and renewable electricity generation capacity in non-OECD countries are particularly important, because they suggest that these factors will play a key role in determining renewable energy innovation in the developing world.

[Table 3 about here.]

There are reasons to believe that our results on political institutions are at best preliminary. First, the only autocratic member of the OECD in our sample is Mexico, and so the interaction effect is based on a comparison of Mexico versus the rest of the OECD. Mexico also happens to be one of the least innovative OECD countries with only 24 patents during years 1990-2009. Second, corruption levels are much lower in OECD countries but vary more than in non-OECD countries.[5]

4.3 Variation Across Renewable Energy Industries

As a final step, we analyzed our data for different industries. The OECD database provides numbers for different types of renewable energy patents. Summing over the OECD categories, we considered wind (one category), solar (thermal; solar photovoltaics), and hydroelectricity patents (tidal, stream, or damless; other marine; conventional hydro). The results are reported in Table 5. The table shows that oil prices increase wind and solar innovation, whereas there is no effect on hydroelectricity. This is understandable because the profitability of hydroelectricity depends on geographic factors to a greater extent; moreover, technologies like marine and tidal energy are not commercial yet, and so last year's oil prices may not be important. Interestingly, renewable electricity capacity has a larger effect on solar and hydro than on wind. This may reflect the fact that the global market for wind technology has been mature for years, while the global market for solar and advanced hydro technologies remains small. The effects of democracy and corruption are inconsistent; the differences across the industries may be spurious because it is not clear why political institutions would have different effects across industries.

[Table 4 about here.]

To illustrate differences in the extent to which countries focus on different industries, consider the cases of China, India, and Brazil. China concentrates primarily in wind and solar photovoltaic (PV) innovation. In 2008, 36% of its renewable patents were in wind, 34% in solar (PV), and 24%

[5]On our 7-scale corruption variable, the variance for OECD countries is about 34% higher than for non-OECD countries.

in solar thermal. It has shown its most rapid rate of growth in solar (PV) patents, the number of which increased fivefold between 2004 and 2008. While China does not export much of its wind energy technology, it exports over 95% of its PV energy technology (Liu and Goldstein, 2013). India produced only 22% of China's total renewable patents in 2008. It too concentrates primarily on wind innovation (36% of total renewable patents), followed by conventional hydro energy (34%). India's wind activity is also relatively new (Lewis, 2007), and it held zero wind patents in 2004. While Brazil held a mere tenth of China's total renewable energy patents in 2008, it boasted half of China's conventional hydropower patents.

4.4 Robustness Checks

To demonstrate the robustness of our findings, we implemented several additional checks. First, we exclude patent counts from each of the five regions, Africa, Asia, the Americas, Europe, and Oceania separately. As another test, we exclude country-years with zero patents to mimic a zero-inflation model; we also drop outlier countries with patent counts of more than 1.5 standard deviations above the mean. Additionally, we include more control variables. We use capital account openness (Chinn and Ito, 2006) and the KOF globalization index (Dreher, 2006) to proxy how embedded a country is into the international system. Controls on the investment profile from the *International Country Risk Guide* and executive constraints from the World Bank's Database of Political Institutions (Beck et al., 2001) account for domestic institutions, while dummies on EU membership and Kyoto Protocol ratification capture a country's international institutions. To account for the link between education and innovation activity, we include a country's logarithmized total expenditures on education and the share of the working population with tertiary education as separate control variables. Lastly, we use the cumulative count of projects registered under the Clean Development Mechanism to proxy for learning effects and increasing technological prowess. While we relegate the details of these robustness checks to the supplementary appendix, these additional regression models strongly support the robustness of our results. The impact of oil prices and renewable electricity capacity remain strong and show the predicted signs, while corruption continues to have an insignificant effect. As already indicated above, the empirical evidence for the role of democratic institutions remains mixed; the effect of our democracy dummy is highly sensitive to the exact model specification.

5 Conclusion

We have examined the economic and political determinants of global renewable energy innovation, 1990-2009. We have found that corruption does not have large effects on a country's production of international patents in the field of renewable energy. Democracy has a large expected effect in some models, but this finding is not completely robust. Domestic renewable electricity generation capacity and high oil prices consistently predict innovation in renewables.

These results bode well for future energy innovation. As renewable electricity generation continues to grow in different markets, including developing countries, innovative capacity may soon follow. High oil prices may also be here to stay due to growing demand from rapidly industrializing countries, and they induce renewable energy innovation across the world.

One policy implication of our work is that simply deploying renewable energy may promote innovation in developing countries and that it is likely to take an even greater effect in these countries than in countries that are members of the OECD. While our analysis does not capture the causal mechanism driving this process, it seems plausible that domestic deployment creates demand for domestic technology production, which in turn spurs the growth of innovation systems in the country. Accordingly, measures to promote the deployment of renewable energy, especially in countries that have historically had little capacity, could contribute to both production and innovation. Ideally, a virtuous cycle of innovation and production would ensue.

Our analysis paints a picture of wind patents primarily responding to increased oil prices, but solar and hydro patents resulting also from increased renewable electricity capacity. This suggests that as oil prices increase, China will continue to invest in wind and solar technology. Further exploration of these trends will speak to the experiences of individual countries and which technologies are likely to take root.

Our study is a preliminary step toward an improved understanding of renewable energy innovation on a global scale, and we are aware of some important shortcomings that are best thought of as opportunities for future research. One such issue is clearly the role of intellectual property rights (Park, 2008; Ockwell et al., 2010). We have focused on broader structural factors and do not have access to detailed data on intellectual property rights (IPR) protection for renewable energy technologies. From a policy perspective, the collection and analysis of such data is a natural next step. Our empirical model offers a plausible baseline for identifying the marginal effect of improved IPR protection on renewable energy innovation.

Another issue is technology transfer. While we focus on highly valuable international patents, a related question pertains to the transfer of existing technologies (Johnstone et al., 2010; Dechezleprêtre et al., 2011). It would be interesting to compare the effects of political and economic factors on innovative versus absorptive capacity, for example. Our empirical model, again, provides a useful point of departure for such an exercise.

References

Akaike H. A new look at the statistical model identification. IEEE T Automat Contr 1974;19:716–23.

Archibugi D, Pianta M. Measuring technological change through patents and innovation surveys. Technovation 1996;16:451–68.

Basberg BL. Patents and the measurement of technological change: A survey of the literature. Res Policy 1987;16:131–41.

Beck T, Clarke G, Groff A, Keefer P, Walsh P. New tools in comparative political economy: The database of political institutions. World Bank Econ Rev 2001;15:165–76.

Bueno de Mesquita B, Smith A, Siverson R, Morrow J. The Logic of Political Survival. MIT Press, 2003.

Burnham KP, Anderson DR. Multimodel inference: Understanding AIC and BIC in model selection. Sociol Method Res 2004;33:261–304.

Cheibub JA, Gandhi J, Vreeland JR. Democracy and dictatorship revisited. Public Choice 2010;143:67–101.

Cheon A, Urpelainen J. Oil prices and energy technology innovation: An empirical analysis. Global Environ Polit 2012;22:407–17.

Chinn MD, Ito H. What matters for financial development? capital controls, institutions, and interactions. J Dev Econ 2006;81:163–92.

Dechezleprêtre A, Glachant M, Hascic I, Johnstone N, Ménière Y. Invention and transfer of climate change-mitigation technologies: A global analysis. Rev Environ Econ Policy 2011;5:109–30.

Dreher A. Does globalization affect growth? evidence from a new index of globalization. Appl Econ 2006;38:1091–110.

Huber J. Pioneer countries and the global diffusion of environmental innovations: Theses from the viewpoint of ecological modernisation theory. Global Environ Polit 2008;18:360–7.

Jaffe AB, Palmer K. Environmental regulation and innovation: A panel data study. Rev Econ Stat 1997;79:610–9.

Johnstone N, Hascic I, Popp D. Renewable energy policies and technological innovation: Evidence based on patent counts. Environ Resour Econ 2010;45:133–55.

King G, Tomz M, Wittenberg J. Making the most of statistical analyses: Improving interpretation and presentation. Am J Polit Sci 2000;44:341–55.

Lanjouw JO, Mody A. Innovation and the international diffusion of environmentally responsive technology. Res Policy 1996;25:549–71.

Lee J, Veloso FM, Hounshell DA, Rubin ES. Forcing technological change: A case of automobile emissions control technology development in the US. Technovation 2010;30:249–64.

Lewis JI. Technology acquisition and innovation in the developing world: Wind turbine development in China and India. Stud Comp Int Dev 2007;42:208–32.

Lewis JI, Wiser RH. Fostering a renewable energy technology industry: An international comparison of wind industry policy support mechanisms. Energ Policy 2007;35:1844–57.

Li Q, Reuveny R. Democracy and environmental degradation. Int Stud Quart 2006;50:935–56.

Liu J, Goldstein D. Understanding China's renewable energy technology exports. Energ Policy 2013;52:417–28.

Mauro P. Corruption and growth. Q J Econ 1995;110:681–712.

Neuhoff K. Large-scale deployment of renewables for electricity generation. Oxford Rev Econ Pol 2005;21:88–110.

Neumayer E. Do democracies exhibit stronger international environmental commitment? a cross-country analysis. J Peace Res 2002;39:139–64.

Newell RG, Jaffe AB, Stavins RN. The induced innovation hypothesis and energy-saving technological change. Q J Econ 1999;114:941–75.

North DC, Weingast BR. Constitutions and commitment: The evolution of institutional governing public choice in seventeenth-century england. J Econ Hist 1989;49:pp. 803–832.

Ockwell DG, Haum R, Mallett A, Watson J. Intellectual property rights and low carbon technology transfer: Conflicting discourses of diffusion and development. Global Environ Chang 2010;20:729–39.

Olson M. Power and Prosperity. Basic Books, 2000.

Park WG. International patent protection: 1960-2005. Res Policy 2008;37:761–6.

Popp DC. The effect of new technology on energy consumption. Resour Energy Econ 2001;23:215–39.

Porter ME, Linde Cvd. Toward a new conception of the environment-competitiveness relationship. J Econ Perspect 1995;9:97–118.

Rose-Ackerman S. Corruption and Government: Causes, Consequences, and Reform. New York: Cambridge University Press, 1999.

Shleifer A, Vishny RW. Corruption. Q J Econ 1993;108:599–617.

Villar J, Joutz F. The relationship between crude oil and natural gas prices; 2006. United States Energy Information Administration.

Wintrobe R. The Political Economy of Dictatorship. New York: Cambridge University Press, 1998.

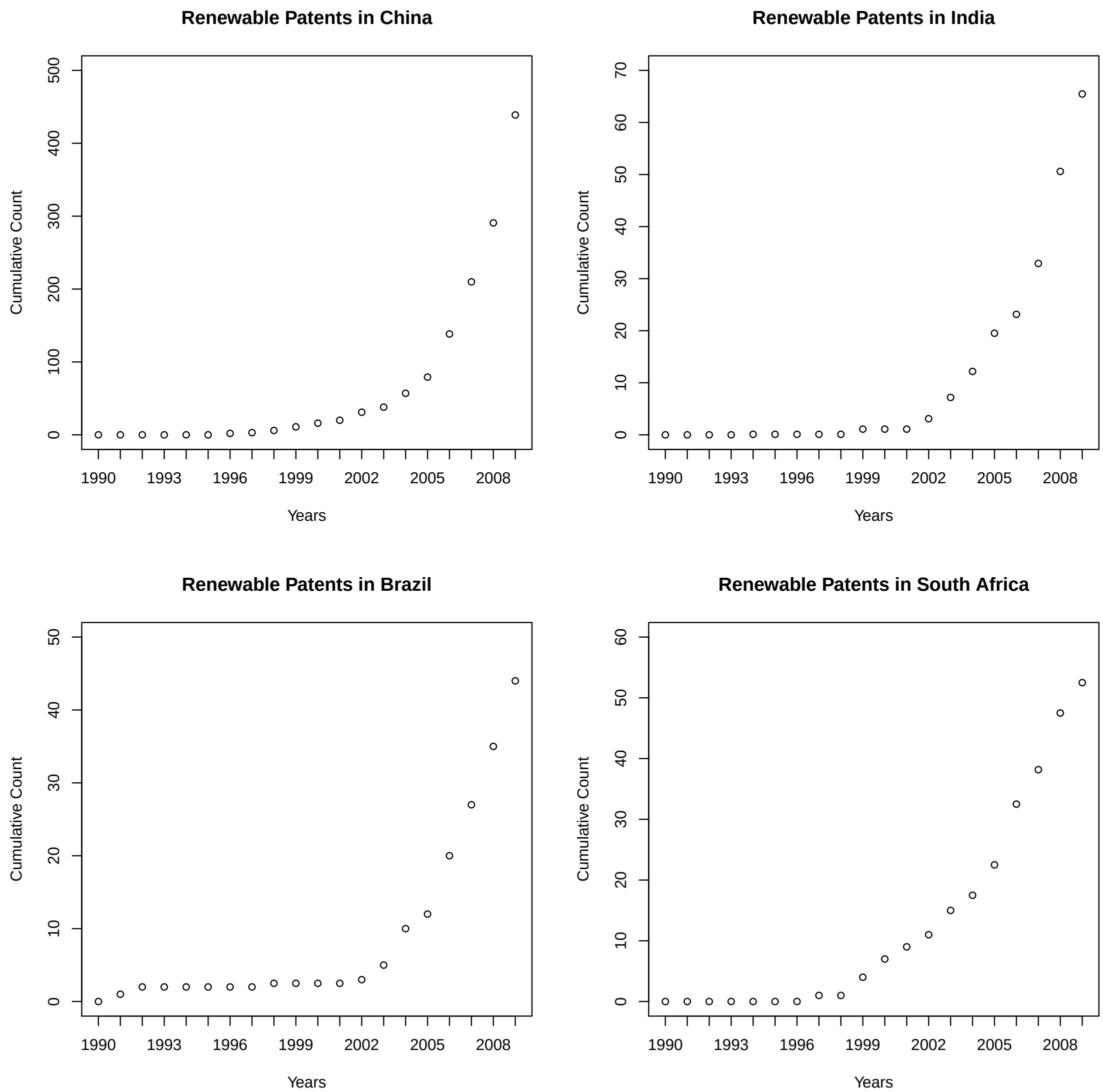

Figure 1: Cumulative count of renewable energy patent applications filed under the 1976 Patent Cooperation Treaty in China, India, Brazil, and South Africa, 1990-2009.

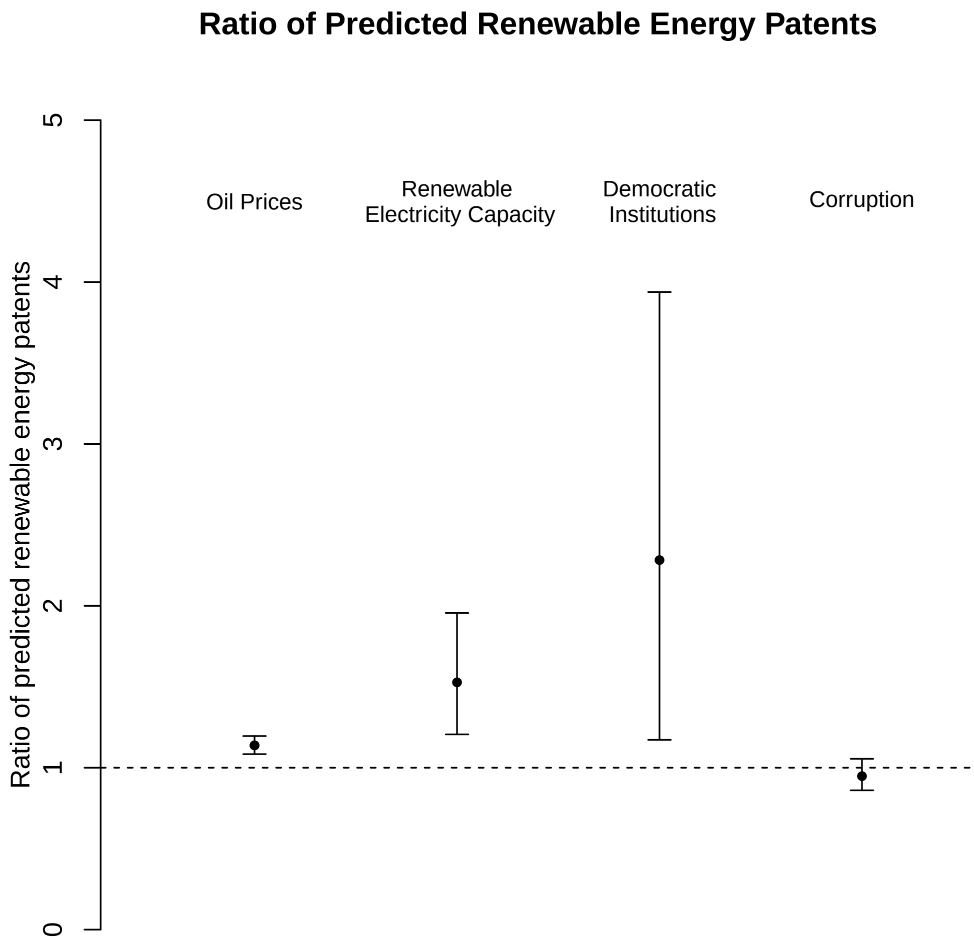

Figure 2: Substantive effects from model (4). This figure shows substantive effects as ratios of expected patent counts for increases from the mean to one standard deviation above the mean for oil prices, renewable electricity capacity, and corruption, while the regime type dummy is changed from autocracy to democracy. All simulations are based on 1,000 draws from a multivariate normal distribution, where continuous variables are held at their means and binary variables at their median values. Error bars indicate 95% confidence intervals.

Summary statistics

	count	mean	sd	min	max
Renewable patents count	1224	12.54	53.53	0.00	874.59
Oil prices (lagged)	1224	40.64	21.55	17.01	98.50
Renew electricity capacity (lagged, logged)	1224	3.84	3.10	0.00	10.58
Democracy (lagged)	1224	0.79	0.41	0.00	1.00
Corruption (lagged)	1224	2.63	1.41	0.17	6.17
OECD membership (lagged)	1224	0.43	0.50	0.00	1.00
GDP (lagged, logged)	1224	25.37	1.68	20.96	30.09
FDI (pct GDP, lagged)	1224	6.87	35.23	-15.05	564.92
Sum of imports and exports (pct GDP, lagged)	1224	78.94	49.59	13.75	438.09
Urban population (pct total, lagged)	1224	66.06	18.13	15.10	100.00
Urban air pollution (PM10, lagged)	1224	42.73	31.33	5.56	213.96

Table 2: Summary statistics for renewable energy innovation. The numbers are based on the model that includes all the control variables discussed above.

Main Results

	(1) Model	(2) Model	(3) Model	(4) Model	(5) Model
Oil prices (lagged)	0.006***	0.005***	0.012***	0.006***	0.005***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Renew electricity capacity (lagged, logged)	0.181***	0.152***	0.133***	0.132***	0.159***
	(0.035)	(0.042)	(0.039)	(0.039)	(0.041)
Democracy (lagged)	0.887***	0.905**	0.957**	0.773**	0.087
	(0.314)	(0.363)	(0.372)	(0.313)	(0.366)
Corruption (lagged)	-0.036	-0.030	0.027	-0.039	-0.018
	(0.040)	(0.044)	(0.044)	(0.038)	(0.039)
OECD membership (lagged)	-0.617**	-0.630*	-0.412	-0.712***	-0.875***
	(0.267)	(0.322)	(0.279)	(0.261)	(0.258)
GDP (lagged, logged)				0.269***	0.079
				(0.095)	(0.113)
FDI (pct GDP, lagged)					0.003
					(0.002)
Sum of imports and exports (pct GDP, lagged)					-0.003*
					(0.002)
Urban population (pct total, lagged)					0.010
					(0.008)
Urban air pollution (PM10, lagged)					-0.032***
					(0.006)
Constant	-3.192***	-3.561***	-3.118***	-9.939***	-3.517
	(0.351)	(0.452)	(0.396)	(2.406)	(3.167)
Region Fixed Effects	Yes	Yes	Yes	Yes	Yes
Linear Time Trend	Yes	Yes	Yes	Yes	Yes
AIC	2.673	2.914	2.445	2.711	2.849
Relative model likelihood	0.891	0.790	1.000	0.875	0.816
Observations	1378	1062	1212	1356	1224

Standard errors in parentheses
Dependent variable: Renewable patents count.
Model (2) excludes years before 1995.
Model (3) excludes years after 2007.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
The AIC is normalized by the number of observations to account for differences in sample size.

Table 3: Main results from fixed-effects negative binomial models.

Main Results from Interaction Models

	(1) Model	(2) Model	(3) Model	(4) Model
Oil prices (lagged)	0.009***	0.006***	0.006***	0.006***
	(0.002)	(0.001)	(0.001)	(0.001)
Renew electricity capacity (lagged, logged)	0.183***	0.260***	0.181***	0.177***
	(0.036)	(0.050)	(0.035)	(0.036)
Democracy (lagged)	0.854***	0.926***	0.851**	1.026***
	(0.319)	(0.319)	(0.334)	(0.328)
Corruption (lagged)	-0.042	-0.046	-0.037	0.077
	(0.040)	(0.040)	(0.040)	(0.074)
OECD membership (lagged)	-0.529*	-0.293	-0.941	-1.222***
	(0.271)	(0.306)	(1.068)	(0.427)
OECD x Oil price	-0.003*			
	(0.002)			
OECD x Renewable electricity capacity		-0.119**		
		(0.054)		
OECD x Democracy			0.338	
			(1.072)	
OECD x Corruption				0.151*
				(0.084)
Constant	-3.245***	-3.403***	-3.169***	-3.605***
	(0.355)	(0.366)	(0.358)	(0.426)
Region Fixed Effects	Yes	Yes	Yes	Yes
Linear Time Trend	Yes	Yes	Yes	Yes
Observations	1378	1378	1378	1378

Standard errors in parentheses
Dependent variable: Renewable patents count.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Results from fixed-effects negative binomial models with OECD interaction effects.

Main Results for Wind, Solar, and Hydroelectricity Patents

	(1) Model Wind	(2) Model *Solar*	(3) Model *Hydro*
Oil prices (lagged)	0.008***	0.007***	0.001
	(0.002)	(0.002)	(0.002)
Renew electricity capacity (lagged, logged)	0.099*	0.207***	0.204***
	(0.054)	(0.044)	(0.057)
Democracy (lagged)	0.650	0.464	1.237**
	(0.523)	(0.399)	(0.565)
Corruption (lagged)	0.121**	-0.128**	-0.110*
	(0.059)	(0.053)	(0.060)
OECD membership (lagged)	0.483	-0.585*	-0.115
	(0.527)	(0.339)	(0.462)
Constant	-4.657***	-3.352***	-4.268***
	(0.457)	(0.436)	(0.577)
Region Fixed Effects	Yes	Yes	Yes
Linear Time Trend	Yes	Yes	Yes
Observations	1178	1238	1148

Standard errors in parentheses
Dependent variable: Renewable patents count.
Model (1) uses wind patents counts.
Model (2) uses solar patents count.
Model (3) uses hydro patents count.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Results from fixed-effects negative binomial models for wind, solar, and hydro patents.