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Essays on Environmental Policy and Technological Change

by

Sahar Milani

A Dissertation Submitted in

Partial Fulfillment of the

Requirements for the Degree of

Doctor of Philosophy

in

Economics

at

The University of Wisconsin-Milwaukee

May 2015

ABSTRACT

Essays on Environmental Policy and Technological Change

by

Sahar Milani

The University of Wisconsin-Milwaukee, 2015
Under the Supervision of Professor Rebecca Neumann

This dissertation is comprised of three empirical essays on technological change. The first chapter examines how industrial R&D intensities respond to environmental regulations when considering specific industry characteristics such as pollution intensity and immobility. Specifically, I study the impact of environmental regulations on R&D intensities in 21 manufacturing industries in 28 OECD countries from 2000-2007. I consider pollution intensity and the relative ease of relocation (immobility) as industry characteristics that determine the optimal industry response to increased environmental policy stringency. I find that more pollution intensive industries innovate less as regulatory environments become more restrictive relative to less pollution intensive industries. At the same time, more immobile industries innovate more than more mobile industries as environmental regulations become more stringent, illustrating innovation as an alternative to relocation. In the second chapter, I investigate how energy prices and production, government investment in R&D, and similarities in environmental regulations may influence international collaboration on energy patents. I study the propensity to collaboratively innovate by examining counts of renewable energy and alternative energy patents from 1994-2008 that have multiple inventors that are located in more than one country. Using a gravity model framework, I demonstrate that technological similarity, com-

mon languages, trade relationships, and similarity in environmental regulations are important drivers of collaboration in these technologies. When examining collaboration between advanced and developing countries, however, higher production of natural gas in developing countries and stronger environmental regulations in advanced nations positively affects the probability of collaboration. The third chapter explores the role of international financial openness on industrial R&D intensities. International financial integration may provide an important channel of financing for research and development (R&D) that ultimately enhances economic growth. This chapter extends the analysis of Maskus et al. (2012) by examining the impact of refined measures of international financial openness, capital controls, and financial structure on R&D intensities in 22 manufacturing industries in 18 OECD countries for the period 1990-2003. We interact these country-level financial measures with industry characteristics, namely dependence on external financing and the amount of tangible assets. Our findings indicate that multiple capital openness indices and financial structure measures are important determinants of R&D intensity. These refined measures indicate that the significance of FDI as an international financial development measure is driven primarily by external FDI assets. This may indicate that multinational firms are able to access funds from affiliate firms abroad, and use such funds as an important source of financing R&D expenditures.

For my father

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Finally, I would like to extend a special thank you to my colleagues in the economics department at the University of Wisconsin - Milwaukee for their tremendous friendship and support throughout this challenging process.

Chapter 1

The impact of environmental policy stringency on industrial R&D conditional on pollution intensity and relocation costs

1.1 Introduction

The relationship between environmental regulations and industry behavior has received recent attention within the field of environmental economics. A growing body of literature indicates that stringent environmental regulations encourage industrial innovation, as technological advancements lower the cost of pollution abatement (Jaffe et al., 2002; Popp et al., 2010). This has important social implications since innovation may help control environmental damage caused by climate change (Popp et al., 2010). By contrast, research that focuses on trade and capital flows provides evidence that dirty industries may relocate, rather than innovate, to countries with less stringent environmental regulations, creating concentrations of polluted geographical areas known as "pollution havens" (Copeland and Taylor, 2004). Thus, more stringent environmental regulations may increase or decrease innovative activities. This paper contributes by providing a closer examination of the characteristics that may determine whether an industry innovates or relocates in response to environmental regulations.

More specifically, I examine empirically how cross-country differences in environmental regulations contribute to industrial research and development (R&D) as a fraction of industry output for pollution intensive manufacturing industries. I employ the methodology introduced by Rajan and Zingales (1998), which utilizes interactions between industry characteristics and country-level measures to study within-country differences among industries. Though widely used to examine finance, growth, and other macroeconomic outcomes, this methodology has not been applied directly to the topic of induced innovation and environmental regulations. I loosely follow the framework of Maskus et al. (2012), who modify the Rajan and Zingales (1998) approach to study the effects of financial development on industrial R&D intensity. I focus, however, on how environmental regulations interact with specific industry characteristics to affect R&D intensities.

To quantify the strength of environmental regulations in each country, I utilize an index of perceived environmental regulatory stringency by corporate executives in 28 countries. This data, provided by the World Economic Forum, is available for the years 2000 to 2007. I interact this measure with two industry characteristics that may be important in determining the response to such regulations. The first industry characteristic is a measure of pollution intensity, which proves useful for determining if R&D intensity is higher in industries that are "dirtier" within countries that have stronger environmental regulations. The idea, first introduced by Hicks (1932), that increases in relative factor prices can induce cost-saving technological change provides further justification for the inclusion of a pollution intensity measure. Since environmental regulations make polluting inputs more expensive, the innovative response of industries is likely to vary based on their comparative usage of these inputs.

The second industry characteristic is a measure of industry immobility as used by Ederington et al. (2005) to capture how variation in relocation costs may affect innovation. Though much of the early work concerning pollution havens indicates a relatively small effect of environmental regulations on industry competitiveness (Jaffe et al., 1995), Ederington et al. (2005) provide evidence that immobile industries are less sensitive to environmental costs when it comes to relocating production, masking the true effects of environmental regulations on international trade. To explore this potential, I utilize the ratio of fixed plant costs (structures) to the value of total shipments for each industry. The intuition is that industries that devote a higher percentage to structures will be less likely to move production when faced with tougher environmental regulations because it is costly to do so.

The main results of this paper can be summarized by the following. I find that industries that are more pollution intensive innovate less under more stringent regulations relative to less pollution intensive industries. This result, however, is partially contingent upon the the relative ease of relocation. I find that industries that are less "footloose" innovate relatively more as environmental regulations increase in stringency. The immobility channel has a larger effect on R&D intensity than the pollution intensity interaction. Quantitatively speaking, the R&D intensity of an industry that is very immobile in a country with strong environmental regulations is 3.77 to 4.93 percentage points higher than that of an industry that is less immobile in a country that has weaker environmental regulations. When compared to the average R&D intensity of 1.65%, this result looks quite large. At the same time, the direct effect of environmental regulations is found to have a negative impact on R&D intensities, illustrating the possibility that regulations impose costs that shift funds away from innovative activities.

Prior research that investigates the notion of induced innovation and environmental policy motivates this study. A series of case studies examined by Porter and van der Linde (1995) provide anectodal evidence that environmental policy induced innovation can simultaneously mitigate the increased costs of regulation while improving efficiency and productivity. Jaffe and Palmer (1997) empirically investigate this claim by analyzing the relationship between pollution abatement expenses and two innovative measures, R&D expenditures and patenting, for a panel of U.S.

industries from 1974 to 1991. Abatement expenses are used as an industry level proxy for the strength of environmental regulations. While they find that there is a significant positive relationship between abatement expenditures and R&D expenditures once industry specific effects are controlled for, they find little evidence for a significant relationship between abatement expenditures and general patenting. Lanjouw and Mody (1996) and Brunnermeier and Cohen (2003) look specifically at environmentally related technology by utilizing international patent classifications. Lanjouw and Mody (1996) document a positive relationship between abatement costs and environmental patenting for Japan, Germany, United States, and 14 low and middle-income countries. Brunnermeier and Cohen (2003) find a relatively small effect, illustrating that environmentally related patents increase by 0.04% when pollution abatement expenditures increase by $1 million. Recent work by Johnstone et al. (2012) indicates that greater policy stringency has a positive effect on environmental patenting in a panel of 77 countries across seven years, using the same environmental policy stringency index that is used in this paper. They find that a one unit increase in environmental regulations induces a 6% to 19% increase in high-value environmental patents.

This paper also relates to recent literature regarding pollution havens and industrial location decisions. Kellenberg (2009) finds robust confirmation of a pollution-haven effect once the endogenous determination of environmental, trade, and intellectual property rights policies are controlled for. He also finds further evidence that more mobile industries are likely to be affected more significantly by environmental regulations when it comes to relocation. Wagner and Timmins (2009) control for FDI agglomeration externalities and find evidence of pollution-haven effects in the German chemical industry. Thus, there is empirical evidence that environmental policy may induce both innovation and relocation. While much of the literature analyzes these effects as separate topics, I contribute by studying them jointly.

The rest of this paper is organized as follows. Section 2 describes the methodology while section 3 discusses the data. Section 4 illustrates the results, with sensitivity analysis in section 5. Concluding remarks and policy implications are presented in section 6.

1.2 Methodology

In this paper I examine the effect of environmental regulations on R&D intensity, measured by R&D expenditures as a fraction of industry output, in industries that are ranked by (i) emissions of different types of air pollutants (ii) their ability to relocate (immobility). The first industry characteristic, pollution intensity, describes the relative cost of compliance with environmental regulations. I assume that industries that are more pollution intensive will have higher abatement costs, based on prior empirical findings. For example, Eskeland and Harrison (2003) report a statistically significant correlation of 0.80 between pollution emission intensities, measured by total toxic releases, and pollution abatement costs among four-digit ISIC sectors in the United States. Cole and Elliott (2005) report that pollution abatement operating costs are highest for the petroleum, primary metals, paper, and chemical industries in the U.S., four of the most pollution intensive industries in my sample. The second industry characteristic, immobility, measures the ease of relocating production to a foreign country. The assumption, based on the work by Ederington et al. (2005), is that industries with higher fixed plant costs (structures) will be less likely to move production because it is costly to do so. In other words, a larger investment in structures discourages an industry from relocating because it would require a significant investment, the construction of a new plant, in the new country (Ederington et al., 2005).

I interact these two industry characteristics with environmental policy stringency, measured at the country level, to study their impact on R&D intensity. My study builds on work by Jaffe and Palmer (1997), who focus on the impact of pollution abatement expenditures on R&D expenditures for U.S. industries. By contrast, I examine variation in regulation across countries. Jaffe and Palmer (1997) indicate the challenges of specifying a theoretically sound structural or reduced form industry level R&D equation due to difficulties in measuring exogenous determinants of demand and supply, as well as the lack of data related to the real costs of scientists or research equipment. As a consequence they present a very simple reduced form specification, with logged R&D expenditures as the dependent variable, and logged pollution abatement expenditures as the independent variable of interest. Along similar lines I investigate the broad statistical relationship between environmental regulations and innovation, where I further condition this relationship on industry characteristics using the Rajan and Zingales (1998) approach.

The empirical approach used in this paper is similar to that in Maskus et al. (2012) who regress R&D intensities on interactions of industry characteristics with country-level measures of national and international financial development. The inclusion of interaction terms, developed by Rajan and Zingales (1998), allows for the utilization of cross-country variation to examine within-country differences across industries. In this context, it is advantageous for determining if R&D intensity responds more for different types of industries as country-level factors change over time. The country-level variable of interest in this study is the strength of environmental regulations, denoted as stringency below. The interactions deliver predictions about whether industries that are more pollution intensive or more immobile innovate more or less than less pollution intensive or more mobile industries in response to different regulatory environments. The estimating equation is given by:

$$\begin{aligned}\text{R\&D intensity}_{j,k,t} =& \beta_0 + \beta_1(\text{pollution intensity}_k \text{ x stringency}_{j,t}) \\ & + \beta_2(\text{immobility}_k \text{ x stringency}_{j,t}) + \beta_3(\text{industry share}_{j,k,t}) \\ & + \beta_4(\text{stringency}_{j,t}) + \eta_j + \eta_k + \eta_t + \epsilon_{j,k,t}\end{aligned} \tag{1.1}$$

where j indicates countries, k denotes industries, and t represents time. The indicators η_k, η_j, and η_t control for unobserved industry, country, and time-specific effects. R&D intensity is measured as total industry R&D expenditures relative to industry output, across countries and time. Intensities are used in order to control for the relative importance of R&D across industries and to accommodate the cross-country panel dataset. In general, the comparison of R&D expenditures across countries is problematic due to the lack of R&D specific exchange rates (Nat, 2014). The use of R&D intensities, which avoids the issue of currency conversion, is a common approach in the comparison of international R&D statistics. Stringency is a country measure of perceived environmental regulation from the World Economic Forum's Executive Opinion Survey. I include the industry share in GDP to control for different industry patterns across countries and expect β_3 to be negative, as in Maskus et al. (2012), with lower R&D intensities in larger industries. The direct effect of environmental stringency is included in the regression as it varies across both countries and time. The direct effects of pollution intensity and immobility are captured within η_k and are not included as separate variables since they are calculated using U.S. data and do not vary across countries or time. The two industry characteristics, pollution intensity and immobility, are each are interacted with environmental regulatory stringency.

Theoretical work by Ulph (1997) provides a foundation for predictions about the effect of environmental policy stringency on innovation. He shows that an increase in emission taxes raises the marginal benefit from environmental innovation and thus encourages firms to invest in R&D. He also illustrates an indirect effect, where emission taxes raise costs of production, reducing output and the incentive to undertake R&D. Coupled with the aforementioned assumptions, I form the following hypotheses to explain how industry characteristics may influence these two opposing effects.

First, industries that are relatively more pollution intensive will have lower R&D intensities than relatively less pollution intensive industries when environmental regulations increase in stringency because they have higher abatement costs. Thus, "dirtier" industries will be more sensitive to environmental regulations due to the increase in costs described by Ulph (1997). Thus, the coefficient on the interaction of environmental policy stringency and pollution intensity, β_1, is expected to be negative. Second, industries that are more immobile will have higher R&D intensities than more mobile industries when environmental regulations become more restrictive because it is costly to relocate. In other words, the increase in the marginal benefit from environmental innovation described by Ulph (1997) is a more likely outcome for immobile industries. This leads to the prediction that the coefficient on interaction between immobility and environmental policy stringency, β_2, will be positive. The direct effect of environmental policy stringency, β_4, could be positive or negative. Jaffe and Palmer (1997), find a positive effect of pollution abatement expenditures on R&D innovation. Ulph, on the other hand, shows that increased emission taxes could increase or decrease innovation. These hypotheses are restated and tested in section 4.

I use U.S. data to measure the underlying industry characteristics considered in this study, namely pollution intensity and immobility. Although many OECD countries have started to record pollution emissions at the industry level through Pollution Release and Transfer Registries (PRTRs), the availability of this data is limited for the time period considered and is not directly comparable across countries. Significant heterogeneity exists in the types of pollutants reported, industries that are subject to reporting, methods of emission measurement, and reporting thresholds. Data on the specific type of capital used to measure immobility is currently unavailable across nations.

These limitations motivate the use of U.S. data, which provides an adequate proxy for these underlying intensity characteristics across countries. Pollution intensity and immobility are characteristics that represent inherent technological differences across industries that can be used to create a ranking, which is not likely to differ across countries or over time.[1] For example, the U.S. pollution intensity estimates used in this paper are similar in ranking with Cole et al. (2005), who present average pollution intensity data for U.K. manufacturing industries from 1990 to 2000. Basic metals, described by Jaffe et al. (1995) as a high abatement cost industry in 1991, is still one of the most pollution intensive industries in the sample year of 2002, indicating time invariance. According to Copeland and Taylor (2004), the pollution intensity of the dirtiest manufacturing industries does appear relatively stable across countries and pollutants and this fact has been commonly employed in prior empirical work.[2] Rankings based on immobility, which is also assumed to be an inherent industry characteristic, are not likely to differ in a sample that contains only OECD countries that are technologically similar. Using similar reasoning to Rajan and Zingales (1998), I argue that the United States has well-developed environmental regulations and therefore the ranking of industries based on pollution intensity and immobility are those that would exist in equilibrium. It is important to emphasize that it is the ranking of industries based on these two characteristics, rather than the actual levels of pollution emissions or structure related capital

[1] This is similar to the use of U.S. industry characteristics in Maskus et al. (2012) and Rajan and Zingales (1998).

[2] For example, Mani and Wheeler (1998), Hettige et al. (1992), and Eskeland and Harrison (2003) use U.S. pollution intensities to rank or classify industries in cross-country analyses.

stocks, that is critical for interpreting the results of this paper.

Since pollution intensity and immobility are calculated using U.S. data and do not vary over time, my analysis faces a limitation when considering the dynamics of industry characteristics. I cannot, for example, study how these variables change over time in response to policy changes. It is not unreasonable to consider that industrial R&D may partially determine industry specific characteristics. For example, Cole et al. (2005) argue that innovative activities reduce an industry's demand for pollution, and thus reduce the pollution intensity of its production processes. Since pollution intensity and immobility are calculated using U.S. data and do not vary across countries or over time, it is not likely that reverse causality will be a problem. Furthermore, investment in R&D is not likely to cause the ranking of industries over time to change. For example, if investment in R&D allows the basic metals industry to employ cleaner production processes, it is still unlikely that this industry will become less pollution intensive than the relatively clean food and beverage production. As in Maskus et al. (2012), I remove the U.S. from the regression analysis to avoid any feedback effects that may result from including U.S. R&D intensities.

1.3 Data

1.3.1 Research and development

I examine 21 manufacturing industries, shown in Table 1.1, at the two-digit ISIC level in 28 OECD countries over a period of 8 years from 2000 to 2007. Data on R&D intensities come from the OECD's STAN Database and are calculated as total industry R&D expenditures as a fraction of industry production in each country. Industry shares are calculated as industry production divided by GDP.

There is an important caveat that applies when considering R&D as an innovative measure in this context. Similar to Jaffe and Palmer (1997), I cannot distinguish between general R&D expenditures and R&D expenditures used for pollution control or environmental technology. This is due, in part, to the limited availability of environmental R&D data. One exception to this limitation is Magnani and Tubb (2012) who study facility-level green R&D in a cross-section of seven OECD countries. Through an analysis of survey data from over 4,000 facilities, they find evidence that R&D at the industry level encourages firm level environmental R&D through spillover effects.

Alternative measures of innovation, namely patent counts, are often utilized because of their disaggregated nature. Patents not only provide specific information about the identities of the inventor and applicant, but also include a detailed description of the invention (Popp, 2005). This would be advantageous here, as technologies related to environmental processes and pollution control could be clearly identified. In industry specific studies, however, patent data can be problematic as the industry code is not recorded by patenting offices (Jaffe and Palmer, 1997). It is likely that many environmentally related patents would be misclassified to industries that produce environmental products rather than industries that produce metal, paper, or chemicals but invest in pollution control innovation (Jaffe and Palmer, 1997; Johnstone et al., 2012). For this reason, many studies that utilize patent counts aggregate the data by patent classification rather than by industry. For example, Johnstone et al. (2012) examine the impact of environmental regulations on specific types of environmentally related technology selected based on International Patent Classification (IPC) classes. Although concordance tables exist that attempt to link patent descriptions to industry classifications, using patent data in industry specific studies introduces imprecision. As a consequence, here, I rely on R&D intensities as my dependent variable. Research by Popp and Newell (2012) indicates that pollu-

Table 1.1: Industry characteristics ranked by immobility

ISIC	Industry Name	Average R&D Int.	CO Int.	PM Int.	NOX Int.	SO2 Int.	VOC Int.	Total Pollution Int.	Immobility
32	Radio, television and communication equipment	6.288	0.862	0.263	0.618	0.049	1.673	3.576	23.714
27	Basic metals	0.446	821.162	87.430	82.363	215.060	45.570	1254.755	17.470
30	Office, accounting and computing machinery	6.396	0.163	0.035	0.243	0.019	0.298	0.758	16.545
19	Leather, leather products and footwear	0.492	1.339	6.335	3.553	4.408	29.200	45.574	16.066
35	Other transport equipment	2.630	1.870	2.207	3.578	2.862	10.335	20.916	15.765
24	Chemicals and chemical products	3.463	102.820	20.417	66.906	100.731	36.993	334.532	15.549
21	Pulp, paper and paper products	0.271	231.095	77.593	160.596	238.315	96.295	810.128	14.862
17	Textiles	0.541	4.738	6.422	18.043	20.394	14.152	64.078	14.415
26	Other non-metallic mineral products	0.496	291.646	148.687	390.968	275.508	33.090	1145.606	14.124
33	Medical, precision and optical instruments	5.172	1.973	2.369	6.247	26.150	4.042	41.169	13.536
29	Machinery and equipment, n.e.c.	1.896	3.282	1.973	3.274	2.136	8.410	19.140	12.953
23	Coke, refined petroleum products and nuclear fuel	0.326	68.583	24.110	92.279	160.074	59.329	407.296	12.293
25	Rubber and plastics products	0.840	1.540	4.204	3.578	8.086	41.914	59.512	12.032
18	Wearing apparel, dressing and dyeing of fur	0.290	1.086	0.354	0.780	2.777	0.664	5.661	11.803
22	Printing and publishing	0.109	0.477	0.549	0.518	0.060	10.674	12.300	11.398
31	Electrical machinery and apparatus, n.e.c.	2.271	8.452	5.961	2.456	2.563	7.395	26.952	11.079
28	Fabricated metal products, except machinery and equipment	0.482	2.503	3.340	3.202	1.348	22.808	33.403	10.800
20	Wood and products of wood and cork	0.152	120.976	83.565	35.702	4.610	91.934	337.266	10.293
15	Food products and beverages	0.209	21.067	14.675	14.064	20.571	18.942	90.539	10.022
16	Tobacco products	0.316	1.881	1.874	9.175	19.237	7.433	40.986	7.888
34	Motor vehicles, trailers and semi-trailers	1.634	2.125	1.288	1.935	1.069	15.583	22.072	7.723
	Mean	1.653	80.459	23.507	42.861	52.668	26.511	227.439	13.349
	St. Dev.	2.031	188.057	40.330	89.954	89.022	27.729	379.012	3.602
	Min	0.109	0.163	0.035	0.243	0.019	0.298	0.758	7.723
	Max	6.396	821.162	148.687	390.968	275.508	96.295	1254.755	23.714

Average R&D intensity is the industry average over all years (2000-2007) and countries, where R&D intensity is calculated as R&D expenditures divided by industry output for each industry in each country. Immobility is measured as the ratio of real structures capital stock to value of total shipments for the U.S. in 2002. Both measures are expressed in percentage terms. Pollution intensities for the U.S. are measured as total emissions (tons) as a fraction of industry production in 2002. Total pollution intensity sums over all pollution intensities listed plus ammonia (NH_3).

tion control R&D may even occur at the expense of other R&D projects, creating a "crowding-out effect." I do not attempt to separate these effects, however, but reference the importance of total R&D in the broader literature, as a specific channel by which environmental policies affect sustainable development, to provide motivation for this type of broad sectoral study (Acemoglu et al., 2012; Aghion and Howitt, 1998).

1.3.2 Industry characteristics

Pollution intensities are drawn from the U.S. Environmental Protection Agency's 2002 National Emissions Inventory.[3] Emissions are measured in tons per year, and have been aggregated from facility level observations.[4] To create a measure of pollution intensity, total aggregate emissions for each pollutant in each industry, are expressed as a fraction of production, using U.S. data from the OECD. Several different byproducts of industrial fuel combustion are considered, including: carbon monoxide (CO), sulfur dioxide (SO_2), nitrogen oxide (NO_X), and particulate matter (PM).[5] Volatile organic compounds (VOC), pollutants that react with sunlight to create ozone, is also included for comparison (United States Environmental Protection Agency and Standards, 2012). Table 3.5 presents the correlations of U.S. industrial pollution intensities across industries for 2002. In general, some pollutant intensities have strong positive correlations. For example, NO_X and SO_2 emissions have a strong positive association. A similar positive correlation exists for CO and PM. On the other hand, correlations between VOC intensities and other pollutants are considerably smaller. This is likely due to differences in production processes

[3] The EPA's National Emissions Inventory (NEI) data is available for 2002, 2005, and 2008. The 2002 inventory is selected because it is closest to the beginning of the data coverage period of 2000 to 2007. Using the 2005 or 2008 NEI data provides similar results.

[4] Industries are converted from U.S. SIC 1987 to two-digit ISIC using Jon Haveman's industry concordances (2012).

[5] Includes $PM_{2.5}$ and PM_{10}. See United States Environmental Protection Agency and Standards (2012) for more information.

and may suggest varying responses to environmental regulations, motivating the examination of these different measures. I also form a measure of total pollution intensity as a comparative summary measure.

The measure of industry-level immobility, also used by Ederington et al. (2005), is taken from the Bartelsman and Gray (1996) NBER-CES Manufacturing Industry Database. To maintain consistency with the pollution intensity measure, U.S. industry immobility is calculated in the year 2002 as the ratio of real structures capital stock to the total value of shipments. An immobility ratio of 15%, for example, indicates that 15% of the value of that industry's shipments is related to capital that is costly to relocate. Thus, industries with higher ratios of fixed plant costs to shipments are considered more immobile by this measure. Table 1.1 presents the industry characteristics ranked by the immobility measure. The average R&D intensity across countries and time for each industry is also included for comparison. It should be noted that there is no clear association between average R&D intensity, immobility, or pollution intensity. Different industries with high or low average R&D intensities can be pollution intensive, immobile, or have differing rankings regarding each characteristic. No clear relationship can be inferred regarding average R&D intensity, though immobility seems to have a positive association and pollution intensity a negative association. In addition, significant variations exist across industries in terms of pollution intensity. Basic metals, for example, has much higher pollution intensities than all other industries. Generally speaking, Table 3.5 illustrates that there is a weak association between pollution intensity and immobility, indicating more pollution intensive industries may be more immobile. However, the correlations are small overall. It is likely that both of these characteristics, immobility and pollution intensity, are important determinants of the optimal industry response to environmental regulation and indicate the complicated interplay between R&D decisions, location decisions, and environmental regulations.

Table 1.2: Cross-correlation table

Variables	Av. R&D Int.	CO Int.	PM Int.	NO_X Int.	SO_2 Int.	VOC Int.	Tot. Pollution Int.	Immobility	Stringency	EPI	Tax Rev. per Cap.	LRGDP per Cap.	Private Cred.	Law&Order	Tertiary Edu.
Av. R&D Intensity	1.000														
CO Intensity	-0.239	1.000													
	(0.000)														
PM Intensity	-0.328	0.711	1.000												
	(0.000)	(0.000)													
NO_X Intensity	-0.234	0.488	0.882	1.000											
	(0.000)	(0.000)	(0.000)												
SO_2 Intensity	-0.261	0.745	0.840	0.874	1.000										
	(0.000)	(0.000)	(0.000)	(0.000)											
VOC Intensity	-0.441	0.470	0.667	0.429	0.559	1.000									
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)										
Total Pollution Intensity	-0.308	0.875	0.935	0.835	0.943	0.624	1.000								
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)									
Immobility	0.569	0.274	0.104	0.119	0.218	-0.048	0.209	1.000							
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)								
Stringency	-0.004	0.005	0.006	0.004	0.004	0.003	0.005	-0.003	1.000						
	(0.755)	(0.750)	(0.695)	(0.788)	(0.785)	(0.813)	(0.725)	(0.823)							
EPI	-0.004	-0.002	-0.002	-0.001	-0.001	-0.003	-0.002	-0.004	0.631	1.000					
	(0.774)	(0.914)	(0.912)	(0.942)	(0.923)	(0.814)	(0.903)	(0.800)	(0.000)						
Tax Revenues per Capita	0.005	-0.007	-0.009	-0.007	-0.007	-0.008	-0.009	-0.000	0.423	0.391	1.000				
	(0.717)	(0.616)	(0.559)	(0.648)	(0.610)	(0.567)	(0.558)	(0.977)	(0.000)	(0.000)					
Log Real GDP per Capita	0.003	-0.003	-0.003	-0.002	-0.002	-0.002	-0.003	-0.000	-0.005	-0.063	-0.482	1.000			
	(0.823)	(0.843)	(0.819)	(0.877)	(0.877)	(0.869)	(0.833)	(1.000)	(0.702)	(0.000)	(0.000)				
Private Credit	0.006	0.003	0.003	0.002	0.002	0.003	0.003	0.001	0.485	0.268	0.243	0.162	1.000		
	(0.645)	(0.819)	(0.822)	(0.903)	(0.898)	(0.860)	(0.833)	(0.924)	(0.000)	(0.000)	(0.000)	(0.000)			
Law and Order	-0.003	0.010	0.011	0.008	0.008	0.010	0.011	0.001	0.683	0.273	0.359	0.119	0.527	1.000	
	(0.842)	(0.519)	(0.462)	(0.616)	(0.591)	(0.511)	(0.484)	(0.951)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)		
Tertiary Education	-0.006	0.008	0.010	0.007	0.007	0.007	0.009	-0.001	0.114	-0.026	-0.047	0.138	0.164	-0.002	1.000
	(0.705)	(0.582)	(0.517)	(0.632)	(0.623)	(0.623)	(0.538)	(0.969)	(0.000)	(0.076)	(0.001)	(0.000)	(0.000)	(0.898)	

p-values are included in parentheses.

1.3.3 Environmental policy stringency

Environmental policy, as the primary country-level variable, is notoriously difficult to measure. By nature, environmental regulations are multidimensional, varying across pollutants, industries, and countries, and with differing levels of enforcement (Brunel and Levinson, 2013). In most cases, policies are not easily comparable or quantifiable. Because of this difficulty, many papers have a very narrow focus. For example, Popp (2002) examines the effect of energy prices on energy efficient patents within the U.S. Popp (2006) looks specifically at the influence of NO_X and SO_2 regulations on mitigation technology related to these two pollutants.

This paper measures a broader effect by using data from the World Economic Forum's (WEF) Executive Opinion Survey published in the annual *Global Competitiveness Report* for the years 2000-2007. This measure is now widely employed in both the environmental regulation and innovation and pollution haven literature.[6] The specific survey question of interest asks executives the following: How stringent is your country's environmental regulation? (1 = lax compared to most countries, 7 = among the world's most stringent). In my sample, the index ranges from 3.5 to 6.8. Though the WEF has conducted the Executive Opinion Survey for more than 30 years, this specific question regarding environmental policy became available in the year 2000 and was included until 2007, limiting the sample time period.

While this survey variable faces a limitation in that it does not contain information about pollutant-specific regulations, it has distinct advantages. First, Kellenberg (2009) points out that survey administration and data collection is conducted with rigor. For example, the WEF partners with economics departments, research institutes, and businesses to assist in a standardized delivery of the survey at a national level. Once collected, the data are subject to a detailed editing process including measures to ensure representativeness across sectors given the composi-

[6] Examples include the previously mentioned works by Kellenberg (2009), Wagner and Timmins (2009), and Johnstone et al. (2012).

tion of each country's economy.[7] Second, this variable measures the perception of business executives facing environmental constraints in a very broad sense. This is useful because it allows for the study of how perceptions of regulatory stringency affect economic outcomes. Thus, it avoids the issue of considering separately the imposition of regulations versus the enforcement of regulations. Executives that believe that regulations are stringent may be more likely to respond by investing in R&D that is aimed at abatement or cleaner production.

By contrast, much of the previous work on environmental regulations relies on the U.S. Pollution Abatement Cost and Expenditures (PACE) survey data as a proxy for environmental stringency. Although this measure provides a clear look at costs of compliance at the industry level in the U.S., no equivalent measure exists in a cross-country setting. This limits analysis to the United States and a few other developed nations who have conducted similar surveys. Furthermore, PACE itself is subject to wider criticisms. Jaffe et al. (1995) explain the difficulty of estimating capital and operating expenditures that would have occurred in absence of environmental policies. Since firms engage in pollution control for other reasons such as public relations, it is difficult to establish an appropriate baseline for comparison. Johnstone et al. (2012) compare the PACE and WEF measures directly and find a negative correlation between the two. They conclude that PACE data is not a reliable measure of environmental policy stringency. Thus, I use the WEF data to quantify the effect of environmental regulations on R&D intensities. Table 1.3 illustrates the variation in environmental regulations across countries by providing the mean value over time of the WEF index for each country in the sample, ranked from most to least stringent. I further explore the accuracy of the WEF measure in section 5.2, and find that it is comparable to other measures of environmental performance and regulation proxies.

[7] See the WEF Global Competitiveness Report 2007-2008 for more information on survey implementation, data collection, and aggregation techniques.

Table 1.3: Average perceived stringency of environmental regulations over 2000-2007.

Country	Mean	Country	Mean
Germany	6.638	Czech Republic	5.063
Austria	6.413	Slovenia	4.971
Finland	6.338	Ireland	4.963
Switzerland	6.338	Italy	4.938
Netherlands	6.325	Portugal	4.825
Norway	6.150	Slovak Republic	4.763
Luxembourg	6.067	Hungary	4.738
Belgium	5.988	Estonia	4.729
New Zealand	5.963	Spain	4.700
Canada	5.788	Israel	4.575
United Kingdom	5.763	Korea	4.513
Japan	5.750	Poland	3.963
France	5.700	Greece	3.963
Iceland	5.663	Mexico	3.775
United States	5.625		

1 = lax compared to most countries, 7 = among the world's most stringent.

1.4 Results

1.4.1 Benchmark using R&D intensity

Table 2.1 presents the baseline regression of R&D intensity on perceived environmental regulatory stringency interacted with pollution intensity and immobility. The estimator used is OLS, with country, industry, and time fixed effects. The perceived environmental policy stringency variable is interacted with each industrial pollution intensity measure, total pollution intensity and with the immobility measure. A baseline regression without interactions is included for comparison.

I test two specific hypotheses: (i) R&D intensity should be lower for relatively more pollution intensive industries when environmental regulations increase in stringency compared to less pollution intensive industries ($\beta_1 < 0$) (ii) R&D intensity should be higher for industries that are relatively more immobile when domestic environmental regulations increase in stringency compared to relatively more mobile industries ($\beta_2 > 0$). I also examine whether the direct effect of environmental regulations has a positive or negative effect on R&D intensities ($\beta_4 \lesseqgtr 0$). Overall, I

Table 1.4: Regression of R&D intensity on perceived environmental regulatory stringency interacted with pollution intensity and immobility

	No interactions	CO	PM	NO_X	SO_2	VOC	Total Pollution Intensity
Industry Share in GDP	-0.0902***	-0.0751***	-0.0778***	-0.0801***	-0.0766***	-0.0735**	-0.0759***
	(0.0253)	(0.0265)	(0.0225)	(0.0262)	(0.0231)	(0.0293)	(0.0279)
CO Intensity*Stringency		-0.00166***					
		(0.000540)					
PM Intensity*Stringency			-0.00317***				
			(0.000917)				
NO_X Intensity*Stringency				-0.00220***			
				(0.000693)			
SO_2 Intensity*Stringency					-0.00285***		
					(0.00105)		
VOC Intensity*Stringency						-0.0107***	
						(0.00379)	
Total Pollution Intensity*Stringency							-0.000729***
							(0.000201)
Immobility*Stringency		0.121***	0.105***	0.104***	0.114***	0.0925***	0.115***
		(0.0395)	(0.0373)	(0.0309)	(0.0344)	(0.0285)	(0.0305)
Stringency	0.0312	-1.457***	-1.219*	-1.266**	-1.345***	-0.935**	-1.336**
	(0.256)	(0.538)	(0.626)	(0.547)	(0.480)	(0.401)	(0.535)
Constant	1.708	3.109	3.050	3.050	3.108	2.659	2.999
	(1.842)	(2.024)	(2.326)	(2.336)	(2.046)	(1.668)	(2.299)
Country, industry, and time-dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,627	3,390	3,390	3,390	3,390	3,390	3,390
Adjusted R-squared	0.176	0.178	0.178	0.177	0.178	0.178	0.178

Bootstrapped standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

find that pollution intensive industries that are constrained by high costs of relocation innovate as a substitutable response to increases in environmental regulatory stringency.

The coefficients on the pollution intensity interaction terms, β_1, are negative and statistically significant across all pollutants. This indicates that relatively more pollution intensive industries innovate less under stricter environmental regulations than do relatively less pollution intensive industries. Broadly speaking, this provides some suggestive evidence for a pollution-haven effect, as dirtier industries may choose to relocate instead of innovate in response to stronger environmental regulations. The coefficients on the immobility interaction terms, β_2, are positive and statistically significant. This suggests that relatively immobile industries innovate more under stricter environmental regulations than relatively more mobile industries. The magnitudes of these coefficients are relatively similar across pollutants with the exception of volatile organic compounds, which has larger intensities across all industries. This is not surprising, as "dirtier" industries are generally pollution intensive in all pollutants, as inferred in Tables 1.1 and 3.5. As expected, the coefficient on the industry share in GDP is negative and statistically significant.[8]

Interpreting the coefficients on the interaction terms in Table 2.1 is challenging because the stringency measure is ordinal rather than cardinal. It is, however, informative to consider a thought experiment used by both Rajan and Zingales (1998) and Maskus et al. (2012) to provide some insight about the economic magnitude of the coefficients. I determine how much the R&D intensity of the industry at the 75th percentile of pollution intensity exceeds the R&D intensity of the industry at the 25th percentile of pollution intensity if both were moved from a low stringency country (25th percentile; Estonia), to a high stringency country (75th percentile; Belgium), while holding immobility at its mean. The same thought experiment is also applied to the immobility measure. I consider how much the the R&D intensity

[8]Many of the country, industry, and time dummies are also jointly significant.

of the industry at the 75th percentile of immobility exceeds the R&D intensity of the industry at the 25th percentile of immobility if both were moved from a low stringency country (25th percentile) to a high stringency country (75th percentile), holding industry pollution intensity at its mean. Table 1.5 summarizes the magnitude of the estimates in percentage points for each type of pollutant.

Table 1.5: Magnitudes of estimates

Differential in R&D Intensity	
CO Intensity	-0.670
Immobility	4.926
PM Intensity	-0.360
Immobility	4.275
NOX Intensity	-0.445
Immobility	4.234
SO2 Intensity	-0.417
Immobility	4.641
VOC Intensity	-1.994
Immobility	3.766
Total Pollution Intensity	-1.388
Immobility	4.682

Differential in R&D intensity is calculated as the percentage difference between an industry at the 75th percentile of pollution intensity in a high-stringency country (75th percentile) and an industry at the 25th percentile of pollution intensity in a low-stringency country (25th percentile), holding immobility at its mean. The same method is used for immobility, holding each specific industry pollutant at its mean.

The implied percentage point change in R&D intensity varies from -0.36 to -1.99 for pollution intensity. When compared to the average R&D intensity of 1.66%, this effect can be quite large. More interestingly, immobility has a much larger effect than pollution intensity for all pollutants. An increase in environmental policy stringency from the 25th percentile country to the 75th percentile country increases R&D intensity by 3.77 to 4.93 percentage points when comparing an industry at the 25th percentile of immobility to one at the 75th percentile. It is important to note, however, that the direct effect of environmental policy stringency on industrial R&D

intensity, β_4, is negative and highly significant. This may indicate that even though an increase in innovation can occur indirectly through the immobility channel, it is uncertain whether or not it can outweigh the direct effect of environmental policy stringency.

The coefficient on β_4 suggests that stronger environmental regulations may impose direct costs that shift funds away from R&D. Though supported by the theoretical findings of Ulph (1997), this result differs from the empirical result of Jaffe and Palmer (1997), who find a positive impact of environmental regulations on lagged R&D expenditures. Their study, however, looks only at U.S data and uses abatement expenses as a proxy for environmental regulations. Further support for a negative coefficient comes from Robinson (1995), who finds empirical evidence that EPA regulations redirect resources away from productivity-enhancing innovation. It is interesting to note that the coefficient of environmental policy stringency is not significant when no interaction terms are included.

1.4.2 R&D expenditures

One alternative way to measure R&D is to use logged R&D expenditures directly rather than intensities. As a robustness check, to further investigate the significant negative coefficient on environmental policy stringency, β_4, I use logged R&D expenditures as the dependent variable. Since the use of R&D expenditures in place of R&D intensities requires the conversion to a common currency, I utilize the Penn World Table's PPP adjusted exchanges rate to express all values in U.S. dollars. I consider a specification that is similar to the setup of Jaffe and Palmer (1997), and include industry value added as a size control, in place of the industry share of GDP. In addition, I include government R&D, which has a significant impact in Jaffe and Palmer (1997) using U.S. data. I include two columns in Table 1.6, one without interaction terms and one with the two interaction terms, so that the effect

Table 1.6: Log R&D expenditures as the dependent variable

	No Interactions	With Interactions
Log Value Added	0.748***	0.763***
	(0.0293)	(0.0354)
Log Government R&D	-0.150	-0.144
	(0.142)	(0.156)
Log Total Pollution Intensity*Log Stringency		-0.154*
		(0.0849)
Log Immobility*Log Stringency		1.768***
		(0.512)
Log Stringency	0.723*	-3.063**
	(0.434)	(1.346)
Constant	-2.104*	-1.626
	(1.108)	(1.285)
Country, industry, and time-dummies	Yes	Yes
Observations	3,300	3,109
Adjusted R-squared	0.879	0.878

Bootstrapped Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
All variables are expressed in natural logarithms
All variables converted to U.S. dollars using PPP adjusted exchange rates

of environmental policy stringency can be isolated.

Without the interactions terms, the impact of environmental policy stringency on industrial R&D expenditures in Table 1.6 is positive and statistically significant, consistent with the coefficient on abatement expenditures in Jaffe and Palmer (1997). With the interaction terms, however, environmental policy stringency has a significant negative impact, just as it does in Table 2.1. This provides support for the idea that the addition of interaction terms may represent an important omission from prior work. Importantly, the sign and significance of the interaction terms using either R&D intensity or R&D expenditures remain the same, indicating that the interaction of industry characteristics is important. Government R&D is not significant in Table 1.6, presumably because it is captured by the country fixed effects. Value added has a positive impact on R&D expenditures, consistent with Jaffe and

Palmer (1997).[9]

The results utilizing R&D expenditures as the dependent variable may avoid issues related to the "output" component of R&D intensity. For example, it could be the case that if relocation follows an increase in the strength of environmental regulations, output would decline as firms exit the market, leading to an undetermined effect on R&D intensity. It could also be the case that richer economies have a higher demand for environmental regulations, and thus environmental policy stringency could have a negative association with the ratio of R&D to output.[10] Using R&D expenditures avoids these issues and provides an additional link to the theoretical underpinnings in Ulph (1997), which refers to total R&D expenditures. I do not utilize R&D expenditures in the main analysis presented in Table 2.1, however, because R&D expenditures may not be as comparable as R&D intensities across countries.[11]

1.5 Sensitivity analysis

In this section, I consider the robustness of these results. Specifically, I address concerns over lagged values, omitted variables, and the nature of the environmental stringency measure used in this study.

1.5.1 Additional specifications

There may be concern that changes in environmental policy may not have an immediate effect on innovation. To verify this, I regress R&D intensity on industry characteristics interacted with one and two period lagged values of environmental

[9] Performing this analysis using each individual pollutant provides very similar results to those presented in Table 2.1.

[10] I thank two anonymous referees for pointing out this important point.

[11] Utilizing PPPs for R&D comparisons have shortcomings. For example, income and structural differences can lead to PPPs derived from very different baskets of goods and services (Nat, 2014). Using either PPP adjusted, or market exchange rates, may not fully represent comparable costs of R&D across countries.

policy stringency. Table 1.7 presents the results showing only total pollution intensity, as the results are comparable for specific pollution intensities. Though these results are still very similar, in terms of sign, significance, and magnitudes of the coefficients of interest to the results in Table 2.1, the one difference is that the direct effect of stringency is no longer statistically significant. In other words, the direct negative impact of environmental policy stringency appears to be instantaneous, rather than lagged. One caveat is that there is not a lot of time variation in the environmental policy variable due to the fact that the sample period is very short. Thus, the lack of significance on the lagged stringency variable may only be suggestive.[12]

There are several reasons why environmental policies differ across countries. As countries reach a certain threshold level of development, environmental regulations become more important as the demand for environmental quality increases. The environmental Kuznets curve (EKC) literature provides evidence of this link, indicating an inverted U-shaped relationship between pollution and GDP per capita (Grossman and Krueger, 1995). Variations in institutional quality may also play a direct role in the creation and enforcement of environmental policy. Other factors such as education and financial development may contribute not only to the stringency of environmental regulations in a given country, but may also be drivers of industrial R&D. Thus, these factors may represent omitted variables. Because environmental policy is influenced by factors that may also be determinants of industrial R&D intensity, these time-varying controls are added to the baseline specification. Unobserved, time-invariant characteristics such as culture, for example, are still captured by η_j.

Table 1.8 illustrates the baseline regression with added controls. Real GDP per

[12] To account for R&D intensity observations that are left censored at zero, I estimated a series of Tobit models. The coefficients of the interaction terms remain significant in all cases but one. Interestingly, the direct effect of stringency is not significant for all but one case using left censored values.

Table 1.7: Regression of R&D intensity on perceived environmental regulatory stringency interacted with pollution intensity and immobility using different lag structures

	One period lag	Two period lag
Industry Share in GDP	-0.0869***	-0.0926***
	(0.0236)	(0.0275)
Pollution Intensity*Stringency$_{t-1}$	-0.000764***	
	(0.000233)	
Immobility*Stringency$_{t-1}$	0.125***	
	(0.0368)	
Pollution Intensity*Stringency$_{t-2}$		-0.000702**
		(0.000278)
Immobility*Stringency$_{t-2}$		0.115**
		(0.0494)
Stringency$_{t-1}$	-1.086	0.502
	(0.767)	(0.461)
Stringency$_{t-2}$		-1.148
		(0.802)
Constant	1.272	-0.927
	(3.035)	(5.074)
Country, industry, and time dummies	Yes	Yes
Observations	3,224	2,808
Adjusted R-squared	0.179	0.170

Bootstrapped standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

capita is included to control for overall development. Private credit, measured as deposit money banks and other financial institutions as a percentage of GDP, is added to account for differences in domestic financial development across countries. Total tertiary education enrollment, expressed as a percentage of the total five-year age group following secondary school, is included to measure the type of human capital that most directly influences R&D. The institutional measure is comprised of two subcomponents: a measure of the strength and impartiality of the legal system (law) and a measure of popular observance of the law (order). Both measures are scaled from 1 to 3, with 1 indicating weak institutional quality and 3 indicating a strong legal system and observance of the law.[13] Data on GDP, tertiary education, and financial development are from the World Bank's *World Development Indicators 2011*. Institutional measures are obtained through the PRS Group's International Country Risk Guide (ICRG).

All coefficients remain significant and change only marginally in magnitude. Because most of the added country-level variables are not significant, it is likely that these variables do not change significantly across the sample time period and are adequately accounted for by η_j in the original regressions. Overall, the main results are maintained, indicating a robust specification to this set of additional controls.

1.5.2 Measuring environmental policy

I now take a closer look at the WEF index as the proxy for environmental regulatory stringency. As mentioned previously, the advantage of the WEF measure is that it captures the effect of managers' perceptions. It may be the case that perceived stringency is actually much higher than the level of regulation that exists in reality. In this sense, the WEF index may not measure whether or not environmental policy constraints are actually binding. Since this variable measures the perception of

[13] A similar institutional measure that specifically relates to corruption yields nearly identical results.

Table 1.8: Regression of R&D intensity on perceived environmental regulatory stringency interacted with pollution intensity and immobility with time-varying country level controls

	No interactions	CO	PM	NO_X	SO_2	VOC	Total Pollution Intensity
Industry Share in GDP	-0.0959***	-0.0848***	-0.0856***	-0.0880***	-0.0848***	-0.0825***	-0.0844***
	(0.0182)	(0.0287)	(0.0256)	(0.0225)	(0.0257)	(0.0237)	(0.0295)
CO Intensity*Stringency		-0.00147**					
		(0.000647)					
PM Intensity*Stringency			-0.00284**				
			(0.00132)				
NO_X Intensity*Stringency				-0.00192*			
				(0.00101)			
SO_2 Intensity*Stringency					-0.00246		
					(0.00151)		
VOC Intensity*Stringency						-0.00929*	
						(0.00531)	
Total Pollution Intensity*Stringency							-0.000640*
							(0.000349)
Immobility*Stringency		0.120**	0.106**	0.105**	0.114**	0.0948**	0.115**
		(0.0554)	(0.0511)	(0.0528)	(0.0541)	(0.0382)	(0.0538)
Stringency	-0.313	-1.837***	-1.624**	-1.672***	-1.739***	-1.374***	-1.727***
	(0.498)	(0.587)	(0.661)	(0.621)	(0.549)	(0.455)	(0.575)
Log real GDP per capita	-2.352	-2.507	-2.520	-2.472	-2.468	-2.505	-2.509
	(3.461)	(3.543)	(3.189)	(3.136)	(3.443)	(3.233)	(3.598)
Private Credit	0.00942	0.0101	0.0101	0.0101	0.0101	0.0102	0.0101
	(0.00765)	(0.00888)	(0.00793)	(0.00642)	(0.00701)	(0.00725)	(0.00778)
Tertiary Education	0.0711	0.0772	0.0772	0.0771	0.0772	0.0771	0.0772
	(0.0652)	(0.0602)	(0.0619)	(0.0584)	(0.0653)	(0.0541)	(0.0690)
Law and Order	0.500	0.539	0.538	0.537	0.539	0.538	0.539
	(0.354)	(0.427)	(0.358)	(0.340)	(0.392)	(0.339)	(0.418)
Constant	20.46	23.09	23.14	22.67	22.68	22.65	22.99
	(33.56)	(33.13)	(30.14)	(30.20)	(31.89)	(30.46)	(33.67)
Country, industry, and time-dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,033	2,828	2,828	2,828	2,828	2,828	2,828
Adjusted R-squared	0.158	0.159	0.159	0.159	0.159	0.159	0.159

Bootstrapped standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

managers, it may also be endogenous, as perceived stringency is likely to decrease when industries develop new technologies that help reduce the cost of compliance with environmental policies. For this reason I employ a composite index of country level environmental performance as an alternative proxy for stringency. The Yale University Environmental Performance Index (EPI) provides a ranking of countries based on their relative distance from certain environmental policy objectives. The EPI considers 22 separate performance indicators in ten categories that include an assessment of policies related to environmental quality and human health as well as ecosystem sustainability. Countries are ranked based on their "position within a range established by the lowest performing country (0 on a 0-100 scale) and the target (equivalent to 100)" (Emerson et al., 2012, p. 18).

Although this index does not measure environmental regulations directly, it may provide an indirect assessment of policy implementation and enforcement. A country that is highly ranked in regards to environmental performance is likely to have more stringent environmental regulations that are enforced. One weakness of both the EPI and WEF indices is that they measure relative regulatory stringency. For example, if regulations are strengthened in one country but by a smaller amount than in others, the perception of policy stringency could decrease. For this reason, I also consider a more objective measure of environmental regulations, the amount of tax revenue, reported in U.S. dollars, raised through environmentally related taxes per capita which is available from the OECD. The idea is that a country that collects more in environmental regulation related tax revenue per capita is likely to have stronger environmental regulations. Both the EPI and tax revenue variables are positively correlated with the perceived stringency measure from the WEF. Table 3.5 illustrates these correlations along with the correlations of the other time-varying country level variables, while Table A1 provides summary statistics related to these variables.

Table 1.9: Summary statistics

Variable	Mean	Std. Dev.	Min	Max	N
R&D Intensity	1.674	5.052	0	166.856	3760
Industry Share in GDP	2.565	2.843	0	24.062	4886
Stringency	5.332	0.843	3.5	6.8	5026
EPI	61.203	6.513	43.28	77.994	5118
Tax Revenue per Capita	597.204	538.453	-2.261	2579.797	5118
Log Real GDP per Capita	11.123	1.939	8.662	16.795	5118
Private Credit	97.695	51.372	14.672	272.796	5049
Law and Order	5.085	0.815	3	6	4758
Tertiary Education	58.338	17.578	9.805	101.804	4741

Summary statistics for all variables over all years (2000-2007) and countries

Table 1.10 presents three additional specifications. The first column provides the specification that includes total pollution intensity and immobility interacted with the perceived stringency measure used in the main analysis (the last column in Table 2.1). The second column shows total pollution intensity and immobility but uses the EPI index as the measure of environmental policy stringency. The third column interacts the environmental tax revenue variable with pollution intensity and with immobility.

The signs and significance of the coefficients are remarkably similar using these different measures. Aside from differences in magnitudes, which is expected, the perceived stringency index is comparable to these two alternative environmental regulation measures, thus strengthening the conclusions regarding the impacts on R&D intensity. These results not only highlight consistent findings in regards to the interaction terms, but also illustrate that the direct effect of environmental regulatory stringency is negative, whether the WEF stringency measure, EPI index, or environmentally related tax revenue data is used.

Table 1.10: Regression of R&D intensity on regulatory stringency interacted with pollution intensity and immobility using different proxies for environmental regulations

	Perceived Stringency	Yale EPI Index	Tax Revenue Per Capita
Industry Share in GDP	-0.0759***	-0.0852***	-0.0791***
	(0.0196)	(0.0211)	(0.0250)
Total Pollution Intensity*Stringency	-0.000729**		
	(0.000296)		
Immobility*Stringency	0.115**		
	(0.0474)		
Total Pollution Intensity*EPI		-8.86e-05***	
		(1.55e-05)	
Immobility*EPI		0.0141***	
		(0.00308)	
Total Pollution Intensity*Tax Revenue Per Capita			-1.16e-06***
			(3.27e-07)
Immobility*Tax Revenue Per Capita			0.000255***
			(5.64e-05)
Stringency	-1.336*		
	(0.697)		
EPI		-0.155***	
		(0.0602)	
Tax Revenue Per Capita			-0.00419***
			(0.00124)
Constant	2.999	3.971	3.365***
	(2.239)	(3.436)	(1.268)
Observations	3,390	3,826	3,409
Adjusted R-squared	0.178	0.189	0.180

Bootstrapped standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

1.6 Conclusion

This paper provides evidence that the innovative response to environmental regulations is conditional on industry characteristics in a cross-country setting. I find that more pollution intensive industries innovate less than less pollution intensive industries as environmental regulations increase in stringency. This may indicate that dirtier industries relocate rather than innovate. Interestingly, the impact on R&D intensity through the industry immobility channel is much larger than the pollution intensity effect. Industries that are more immobile innovate more than relatively more mobile industries as stricter environmental polices are implemented, indicating that environmental regulations may induce innovation through this channel. I also provide evidence that environmental regulations have a negative direct effect on R&D intensities. Thus, this paper contributes to the literature by providing a broad link between papers that study pollution havens and those that investigate induced innovation, while using a methodology that has not been previously applied in this setting.

Specific policy implications may arise from these results. If the goal is to induce innovation through environmental regulations it may be optimal to target those industries that are unable or less likely to relocate. The important point illustrated in this paper, though, is that immobile industries are not necessarily the most pollution intensive. Consequently, current policies that focus only on pollution output as a restrictive measure may not result in innovative activity.

There is room for additional work on this topic that may be useful in the development of policies. As the sensitivity analysis indicates, these results are robust to additional country level controls and other measures of environmental regulation. Further research that adds a dynamic component to the industry characteristics, as data becomes available, could resolve some of the ambiguity regarding the relationship between industry characteristics, as it would more accurately reflect the timing of policy changes. Decomposing the interconnections between immobility, pollution intensity, and environmental regulations also deserve a closer look in future research and would be useful in the development of effective environmental policies.

Chapter 2

Who innovates with whom and why? Evidence from international collaboration in energy patenting

2.1 Introduction

Renewable and alternative energy technologies have the potential to conserve energy and reduce carbon emissions worldwide. However, progress towards the implementation of these technologies remains stagnant. At the same time, technologies that utilize fossil fuels continue to dominate the energy generation sector. For example, global usage of coal-fired power generation technologies grew 6% from 2010 to 2012, faster than any non-fossil fuel generation technology (IEA, 2013b). This may be attributed, in part, to substantial obstacles to the employment of renewable energy technologies. These barriers include high up-front capital costs, infrastructure requirements, and knowledge limitations (IEA, 2013b). Investment in innovation becomes an important factor in lowering these costs. Collaborative innovation between countries may aid in cost and knowledge sharing, while also promoting the diffusion of renewable and alternative energy technologies.

This issue is particularly important for the developing world, where the consequences of climate change are magnified due to deficiencies in renewable energy technologies and rapid expected growth in energy demand. In fact, energy consumption in non-OECD countries is expected to increase by 84% over the next 25 to 30 years, as access to electricity expands in less developed nations (Wolfram et al., 2012). Given that most of the world's innovative activity is concentrated in a few developed countries (Nagaoka et al., 2010; Eaton and Kortum, 1999), policies that encourage the United States, Japan, and Germany, for example, to spearhead joint research efforts with developing nations could help transfer the necessary knowledge needed to produce energy efficient technologies. Collaboration may be especially important, as recent evidence indicates that knowlege spreads quickly within social networks, where mutual learning develops within research teams (Montobbio and Sterzi, 2013; Hoekman et al., 2009). The purpose of this paper is i.) to examine which countries innovate together to develop renewable and alternative energy technologies and ii.) to study the factors that may contribute, either positively or negatively, to collaborations of renewable and alternative energy technologies at the country level.

To measure collaboration, I examine counts of renewable energy and alternative energy patents that have multiple inventors that are located in more than one country. I obtain these counts from the OECD Regional Patent database, which contains patent applications filed with the European Patent Office (EPO) and filed under the Patent Cooperation Treaty (PCT) international phase. These patents provide a convenient way to study the importance of distance, both technological and physical, on the propensity to collaboratively innovate. Evidence in the broader literature suggests that geographical constraints may localize knowledge spillovers (Keller, 2004; Jaffe et al., 1993) with the transmission of tacit information often requiring person-to-person interaction (Kim et al., 2006). Collaborative patents provide an empirical avenue to study knowledge diffusion because they contain detailed information about the inventors' countries of origin and thus provide an illustration of teams of scientists within global networks (Marsan and Primi, 2012). The disaggregated nature of patent data also makes it possible to identify specific renewable energy sectors, such as solar, wind, and hydro power. This is useful when calculating how similar countries are in terms of the production of renewable energy and alternative energy patents and how this similarity may affect collaboration.

My goal is to investigate the factors that affect collaboration, to shed light on potential policies that may encourage international knowledge diffusion. The importance of distance, which represents the costs of face-to-face communication, motivates the use of a gravity model, commonly employed in international trade and finance. Using the number of collaborative renewable and alternative energy patents as the dependent variable, I include GDP per capita and the total number of patents to account for mass, in terms of economic wealth and innovative activity. I also examine the effects of trade, common languages, and colonial relationships on the propensity to collaborate on renewable energy and alternative energy production technologies. In addition to the aforementioned variables, this paper is the first to consider the influence of energy prices and production, similarity in environmental regulations, and government renewable energy research and development (R&D), in a patent collaboration study that relates specifically to energy related technology.

This paper relates to three lines of literature. First, a subset of the technology diffusion literature explores collaborative patenting. My analysis is most closely related to work by Montobbio and Sterzi (2013) and Picci (2010), who utilize gravity models to study knowledge transfer using collaborative patent data for all technology classifications. Montobbio and Sterzi (2013) find that technological proximity and common language are important determinants of patent collaboration between eleven emerging and seven advanced economies. They find that intellectual property rights positively affect collaboration when joint research occurs within subsidiaries of multinational firms. Picci (2010) also indicates that cultural characteristics such as common languages positively affect patent collaboration, while physical distance negatively impacts patent collaboration. Other work by Maggioni et al. (2007) shows that the similarity of regional innovation structure, R&D expenditures, and spatial proximity significantly impact collaborative patenting in Europe in both a gravity and spatial econometric framework. Hoekman et al. (2009) and Hoekman et al. (2010) examine regional collaboration in Europe using similar gravity models, highlighting the importance of physical distance and institutional factors. Ma and Lee (2008) construct indices based on co-inventorship data from the U.S. Patent Office. Their results illustrate a pattern of increasing patent collaboration for the eight most inventive OECD nations from 1980-2005. On the other hand, Ma et al. (2009), narrow their focus to patent collaborations between China and other high innovation countries, illustrating that these types of research collaborations have steadily increased over time. These studies, however, focus on general patenting in all technology classes. I examine the specific case of renewable and alternative energy patents using this literature to motivate the relevant econometric techniques to study collaborative patenting.

Second, I build upon key ideas related to absorptive capacity that originate from studies of R&D cooperation at the firm level. Miotti and Sachwald (2003), who empirically investigate domestic and international R&D partnerships using survey data from French manufacturing firms, find evidence that firms that are closest to the technological frontier tend to engage in cooperative R&D partnerships more frequently. Cassiman and Veugelers (2002) find that, for Belgian manufacturing firms, incoming knowledge spillovers contribute positively to cooperation. They also find that the permanent level of R&D, a measure of the overall level of R&D capability of a firm, contributes positively to the importance of incoming spillovers. In other words, those firms that already engage in R&D and have a substantial research base are more likely to form partnerships because they can better absorb incoming information. Taking a broader approach by examining collaborative efforts at the country level, I study the varying absorptive capacities of nations as a necessary complementary resource. In the empirical model, I include a measure of the total number of patent applications in all technology types to account for absorptive capacity at the country level.

Third, work that examines the innovation and diffusion of energy technologies provides motivation for the inclusion of energy prices and production, environmental R&D, and environmental regulations as contributing factors to collaboration. The concept, first proposed by Hicks (1963), that increases in relative factor prices can induce cost-saving technological change is investigated in detail in the environmental literature. Environmental regulations, either directly through command and control polices, or indirectly through taxes that increase energy prices, make the employment of pollution intensive technologies more expensive. Many studies find a positive effect of energy prices and regulation on innovative activity (Popp et al., 2010). Newell et al. (1999), for example, find that changes in energy prices and consumer regulatory standards are responsible for significant amounts of innovation in energy-using consumer durables. Using patents from 11 different alternative and energy-efficient technologies, Popp (2002) finds that prices and other regulations that may increase the costs of fossil fuels induce new research at a rapid pace. I take this idea a step further by asking how this cost-saving mechanism, via higher energy prices or environmental regulations, affect collaborations that may aid in the diffusion of environmentally related technologies across, rather than within, countries. The use of collaborative patents differentiates my study from Verdolini and Galeotti (2011), who study international technology diffusion in energy-efficient technologies through geographic and technological channels. They find that distance, whether physical or technological, negatively impacts knowledge flows. While they use patent citations to measure these spillovers, I focus on the importance of person-to-person communication that collaborative patents capture, providing a contribution to the energy patenting literature.

The main findings of this paper can be summarized by the following. I find that technological proximity, common languages, trade relationships, and similarity in environmental regulations are important drivers of international collaboration in renewable and alternative energy patenting. Absorptive capacity, measured by the total number of patents in all technology classes in a given year for each country, has a significant and positive effect on collaboration for both countries in an innovating relationship. I find physical distance to be largely unimportant, suggesting that advances in communication and travel reduce the costs of communication. My results also suggest that higher energy prices may not have a significant impact on collaborative patenting while larger government investment in renewable energy R&D decreases the probability of collaboration. When examining collaboration between developed and developing countries, I find that higher production of natural gas positively affects the probability of collaboration for developing countries, suggesting that in the developing world, countries that have more natural gas resources may be more concerned with the development of efficiency improving technologies that are often utilized to complement renewable technology.

The remainder of this paper is organized as follows. In section 2 I discuss the use of patent data as an innovation indicator and describe the construction of the main data set, drawn from the OECD Regional Patent Database. Section 3 illustrates the methodology and predictions concerning the variables that may affect collaboration. I present the regression results in section 4, followed by concluding remarks in section 5.

2.2 Data

In the following section I describe the main database used to investigate the factors that influence the propensity to collaborate in renewable and alternative energy technologies. I explain the advantages and disadvantages of using patent data at the country level as a measure of innovation. I also explain how I extract patents specific to renewable and alternative energy from the OECD's Regional Patent Database.

2.2.1 Patents and collaborative patents

Patents counts are a widely used measure of innovation output. Patent documents include detailed information about the patent's inventors as well as technology classification information that is necessary for observing environmental technologies (Popp, 2005). This allows me to i.) select patents that are related to renewable and alternative energy production and ii.) identify patents that are internationally collaborative. Figure A1, located in the appendix, provides an example abstract from a collaborative patent used in this study. The abstract contains the date of publication, along with the date on which the initial application was filed, which is known as the priority date. In addition to containing a description of the technology, the abstract also contains an identifying code (IPC) which allows for the selection of specific technologies.[1] Most importantly, the abstract provides the names and country affiliations of all applicants and inventors. Thus, I can use patent counts to identify collaboration between inventors across countries on specific types of technology. By contrast, an alternative measure of innovation, R&D expenditures, are an input measure for the innovation process, and are generally not available for specific environmental technologies. Thus, patent counts are superior for this study.

In this paper, I study applications filed to the European Patent Office. Because significant heterogeneity can exist in the value of inventions that are ultimately patented, I select patents that are also filed under the Patent Cooperation Treaty (PCT), which allows patent applicants to seek protection simultaneously in multiple nations through a unified procedure in each country's national patent office. Filing

[1]This patent application seeks protection for a technology related to solar energy. The identifying IPC code indicates that it is a "device adapted for the conversion of radiation energy into electrical energy" under the code "H01G 9/20" in Table A4. The patent application indicates that one inventor is from China and the other two inventors are from Switzerland. Thus, it is counted as one instance of collaboration for the China-Switzerland country pair in the priority year of 2003.

under the Treaty allows for an alternative route to patenting at the EPO and can be considered a filing process that identifies high value patents since its purpose is to assist with international patent protection (Van Zeebroeck and Van Pottelsberghe, 2011). Other strategies that can help identify high value patents include selecting patents that are highly cited, or using Triadic patents, which are families of related technologies that have been patented simultaneously under three regimes: the US Patent and Trademark Office (USPTO), the Japanese Patent Office (JPO), and the European Patent Office (EPO) (Nagaoka et al., 2010). The idea is that the most valuable patents will be highly cited and that submitting applications in multiple patent offices will serve as a robust quality screening. Directly using citations as a patent value indicator may be less appropriate for this study because citations are not compulsory under the EPO. However, in an empirical patent value study, Van Zeebroeck and Van Pottelsberghe (2011) find that patents filed through the PCT are associated with more patent citations, and are a significant predictor of the likelihood of patents also being Triadic. In other words, using the PCT as an indicator of high value patents is similar to strategies that involve other patent value indicators.

I use a single patent office, the EPO, to avoid complications that could be caused by comparing patents in different regimes. Differences in examination systems and disclosure requirements may affect patent information that is available. For example all patent applications in Europe are automatically disclosed and applicants must request an examination to proceed with their application. By contrast, disclosure in the United States, where all patents are examined automatically, was not introduced until 1999 (Nagaoka et al., 2010). Thus, the use of patent applications to the EPO provides a comprehensive and comparable innovation measure.

While patent data provide the most accurate view of international collaboration that is available, the extent to which patents with inventors in different countries represent actual research collaboration is uncertain. Bergek and Bruzelius (2010) investigate whether patents with multiple inventors in different nations reflect actual cross-country R&D collaborations within the Swiss-Swedish multinational firm ABB. They find that less than half of ABB's internationally collaborative patents represent actual joint research across nations. Through interviews with Swedish inventors, they find that some credited inventors only participate in support roles, such as providing advice, or application writing services, rather than actual R&D activities. They also find that temporary relocation, or relocation after the R&D project is complete may also falsely indicate international collaboration. Their analysis, however, looks only at one firm in a specific case study with only 53 collaborative patents. As Montobbio and Sterzi (2013) point out, inventor movement may still be indicative of international knowledge flows. For example, Kim et al. (2006) study inventor movement in the labor market for scientists and find that collaboration with researchers who have experience in a foreign country can help facilitate access to new technology. Thus, without additional information available on the extent of collaboration, collaborative patents provide at least one measure, albeit imperfect, of such collaboration.

2.2.2 OECD Regional Patent Database

In this study, I focus on energy related technologies to shed light on how collaborative innovations may help mitigate the growing demand for energy in the developing world. To accomplish this, I extract patents related to renewable and alternative energy production from the OECD Regional Patent Database, which contains patent applications filed to the European Patent Office (EPO) and patent applications filed under the Patent Cooperation Treaty (PCT) from 1977 to 2011 for OECD countries, the EU 27 countries, Brazil, China, India, Russia, and South Africa (OECD, January 2013). The database also contains a detailed regional component that links the addresses of applicants and inventors to more than 5,500 regions. Although I do not utilize this aspect of the database directly, regionalization of the data ensures that detailed inventor information is available for each patent, making the Regional Patent Database the most appropriate for this study. Information about the inventors' countries of origin for each patent is drawn from the abstract and is compiled in the database, allowing me to easily identify patents that include inventors from different countries and are thus likely to be collaborative across nations. In order to alleviate concerns about long lag times that can exist between the date of application and the date the patent is granted under the EPO regime, I use the priority year, the year closest to the time of invention, to determine the time component of the panel.

The OECD Regional Patent Database is available to researchers by request from the OECD. Patents are extracted in three steps. First, inventor names and addresses are merged with the corresponding IPC codes and priority years. Second, patents related to renewable and alternative energy technologies are extracted from the database based on identifying IPC codes. Third, patents that have multiple inventors in more than one country are extracted and are subsequently counted in terms of bilateral pairs, at the country level for each year.[2]

I select patents based on International Patent Classification (IPC) codes. Developed by the World Intellectual Property Organization (WIPO), these codes provide a hierarchical structure for attributing patents to different technological categories. These categories include broad groups with subdivisions for more specific technology types. IPC codes are indicated on each patent document and are subsequently included in the OECD Regional Patent Database. To identify the appropriate energy patents, I use IPC codes from two distinct sources. The first selection of IPC codes is related to renewable energy and are from Johnstone et al. (2010), who study

[2]The methodology used for patent extraction in steps 1 and 2 was developed during my time as a research assistant for Itziar Lazkano. I am grateful for her guidance in data construction and for bringing my attention to the importance of renewable and alternative energy technologies.

the effect of environmental policies on renewable energy innovation. After reviewing the literature related to renewable energy advancements, they determine a set of key words that are used to identify relevant IPC codes. These codes and their descriptions are included in Table A3 in the appendix. Though widely used in the literature to identify renewable energy patents, these codes are not comprehensive. I also include IPC codes from the World Intellectual Property Services (WIPO) IPC Green Inventory, listed in table A4. The IPC codes listed in the IPC Green Inventory have been compiled by the IPC Committee of Experts in concordance with the United Nations Framework Convention on Climate Change (UNFCCC), to better facilitate searches of environmentally related patents. Lazkano (2014) and Lazkano et al. (2014) also utilize a subset of these codes to study the transition from fossil fuel to renewable energy technologies. These codes provide the most complete source of IPC codes related to alternative energy production that is available.[3] Using both sets of IPC codes, the broad technology classifications used in this paper to capture both renewable energy and alternative energy include solar, geothermal, ocean and hydro power, fuel cells, biomass and man made waste, biofuels, other production or use of heat, and waste heat.

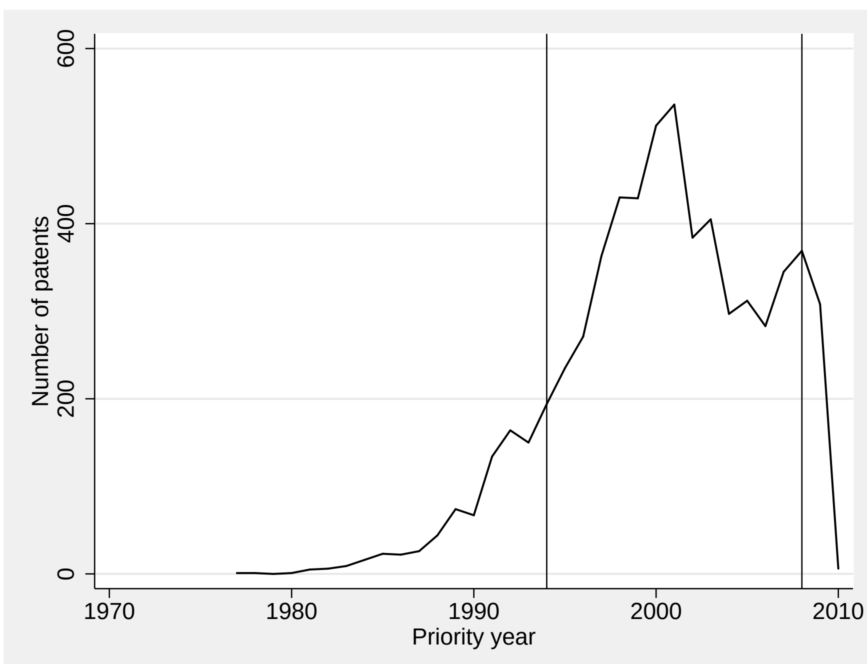
2.2.3 Summary statistics

In total, the full database contains 2,458,535 unique patent applications to the EPO from 1977-2011 that contain inventor credentials, of which 83,674 are collaborative and have been filed through the PCT. Of this subtotal, I extract 5,139 collaborative energy patents. Figure 2.1 illustrates the number of renewable energy and alternative energy collaborative patents from 1977 to 2011. The series exhibits three distinct trends, a steady increase in collaborative patents from 1977 to 2000, followed by declines in 2001, 2003, and 2008. The trends in 2001 and 2003 are consistent

[3] For more information seehttp://www.wipo.int/classifications/ipc/en/est/

with the general trend of renewable and alternative energy patent applications to the EPO. In the broader collaboration literature, Ma and Lee (2008) find a consistently upward trend in general collaborative patenting. However, their sample period ends in 2005. The sharp decline in 2008 is likely due to patent publishing delays. Applications filed using the PCT, in particular, can have a lag time of up to 31 months between the priority date and date of publication (OECD, 2008). For this reason, I exclude patents published after 2008. Because one of the main variables of interest, the level of environmental regulations measured by tax revenue raised from environmentally related taxes, intersects only partially over countries and time with the OECD patent data, I exclude patents published between 1977 and 1993 in my analysis. These sample restrictions are indicated by the vertical lines in Figure 2.1. Given these constraints, I examine 4,265 total collaborative energy patents between 1994 and 2008.

Figure 2.1: Time series of collaborative energy patents



The first objective of this paper is to examine which countries collaborate to develop renewable and alternative energy technologies. Table 2.1 illustrates the top 10 renewable and alternative energy collaborative country pairs in the sample. Given that the leading innovative research economies are the United States, Germany, and Japan, it is not surprising that a large number of collaborations occur between these and other developed nations. The largest number of collaborations occurs between the United States and the United Kingdom. Nagaoka et al. (2010) use data up to 2005 and show that when considering total patenting, as opposed to just environmental patenting, 12% of U.K. patents contained a foreign inventor, larger than both the U.S. (8.3%) and Japan (1.5%). Thus, the importance of both the U.S. and U.K. as collaborative partners is reflected in the larger literature. It is important to note that patent applications do not indicate a leading or following country. Thus, the country listed as country 1 or country 2 in Table 2.1 is arbitrary.

Table 2.1: Top 10 energy patenting collaborative partners

Country 1	Country 2	Total collaborations
United Kingdom	United States	483
Germany	United States	364
Canada	United States	323
Japan	United States	230
France	United States	216
Netherlands	United States	192
Switzerland	Germany	143
Belgium	United States	132
Germany	Netherlands	114
Germany	France	113
Germany	United Kingdom	104

Sample period 1994-2008

Since the motivation for this study relates largely to the growing need for renewable energy technologies in the developing world, it is also relevant to look at collaborative patenting between developing and advanced nations. Table 2.2 presents the top 10 collaborative pairs that consist of one developing and one advanced economy.

I use the classifications for developing and advanced countries from the the World Bank. I consider high income countries to be advanced and low and middle income countries to be developing.[4] For this subsample, the highest number of collaborative patents occurs between the U.S. and China, followed by the U.S. and India. In general, the number of instances of collaboration between the developed and the developing world is small for these types of technologies, and non existent for developing to developing country collaboration. In the following section I describe why this may be the case, as I outline the empirical methodology to explain these trends.

Table 2.2: Top 10 energy patenting collaborative partners between advanced and developing nations

Developing country	Advanced country	Total collaborations
China	United States	59
India	United States	23
China	Germany	18
South Africa	United States	13
India	Germany	13
Brazil	United States	10
China	United Kingdom	9
China	Japan	9
China	Switzerland	8
China	France	8

Sample period 1994-2008

2.2.4 Firm analysis: Applicants vs inventors

In this paper, I focus solely on inventors, who are the main researchers and scientists involved in producing the patented technology. I do not count patents based on their applicants, who hold the legal right to the patent and are often the firm or organization that provides the resources to develop the technology. There are two reasons for this. First, this study relates closely to the diffusion of knowledge

[4]For more information see http://data.worldbank.org/income-level/HIC and http://data.worldbank.org/income-level/LMY.

through the collaboration of research teams. Recent evidence suggests that the transmission of technology often requires person-to-person interaction, facilitated by close proximity (Kim et al., 2006). For this reason, examining the location of the inventors is more appropriate as physical distance represents the cost of face-to-face communication. Second, patent co-ownership may not be an accurate measure of technology collaboration. Multiple applicants, even if they reside in different countries, may be consolidated into a single applicant on the patent application, or a third party may be listed instead (Nagaoka et al., 2010). In this sense, patent applicants only provide partial information about collaboration.

While inventor information is important for identifying collaborative patents, the innovative response to changes in environmental regulations and energy prices is ultimately a firm-level decision. For this reason, I examine the applicant names to determine i.) if these patents represent innovation within multinational firms or true inter-firm collaboration and ii.) the distribution of collaborative energy patents across firms.

Of the 4,265 collaborative energy patents in the sample period, 1,089 (about 26%) have more than one applicant. Within this subsample, some are identifiable as collaboration within multinational firms. One clear example is Swiss miltinational pharmacutical company Novartis, noted as “NOVARTIS AG” in the database. This company appears as a joint applicant with “NOVARTIS PHARMA GMBH” which has an Austrian affiliation, and thus can be denoted easily as a subsidiary firm. However, if the applicants’ names are significantly different, it may be impossible to determine the firm relationship. As one possible measure to estimate the number of collaborative patents that result from inter-firm collaboration, I remove multi-applicant patents that have the same first word in the applicant name. Using this identifying strategy, I find that 952 patents (22%) are representative of across-firm collaboration. Patent applications with only one applicant may be representative of collaboration within multinational firms. While this may be the case, they may also indicate inter-firm collaboration where only one firm name is listed on the patent application. This analysis, albeit limited, suggests that energy patent collaboration occurs both within multinational firms and between firms.

Table 2.3 illustrates the distribution of collaborative energy patents for the top 10 patenting firms. Because more than one firm may be listed on a patent application, patent counts are given in fractional terms, with equal contribution assigned to each applicant. In general, patenting is not largely concentrated in this sample. These innovative firms, consisting of multinationals in the developed world, account for roughly 14% of the total collaborative energy patents in the sample. It is also interesting to note that there are only 50 patent applicants with developing country affilations. These statistics may highlight the importance of multinational firms for technology transfer, however, strong conclusions cannot be drawn due to difficulties in firm name identification. Even if much of the collaboration occurs within multinationals, exploring this collaboration across inventors in different countries may still be useful.

Table 2.3: Top 10 patenting firms 1994-2008

Firm Name	Country	Total collaborative energy patents (1994-2008)
SHELL INTERNATIONALE RESEARCH MAATSCHAPPIJ B V	Netherlands	110.33
EXXONMOBIL RESEARCH AND ENGINEERING COMPANY	United States	82.33
NOVOZYMES A/S	Denmark	69.67
EXXONMOBIL CHEMICAL PATENTS	United States	62.00
BASF PLANT SCIENCE GMBH	Germany	55.33
INCYTE GENOMICS	United States	48.50
BASF SE	Germany	44.50
FORSCHUNGSZENTRUM JULICH GMBH	Germany	39.17
SMITHKLINE BEECHAM CORPORATION	United States	39.02
GENENCOR INTERNATIONAL	United States	37.33
Total		588.18
% of total collaborative energy patents		13.79

Patent counts are fractional because a patent application can have more than one applicant.

2.3 Methodology

In this section, I present an empirical model to explain knowledge flows, embodied through counts of collaborative environmental patents, between inventors located in separate countries. Specifically, I analyze the determinants of collaboration in renewable and alternative energy patents using a gravity model. The gravity model is a frequently used empirical tool, analogous to Newton's gravity law, that indicates that the gravitational force between two objects is dependent on the mass of the objects and the distance between them (Picci, 2010). It is remarkably successful in explaining bilateral trade flows, demonstrating that trade between two countries is increasing in their respective economic sizes, and decreasing in their physical distance (Bacchetta et al., 2012). The gravity model is now widely employed in the research collaboration literature. Montobbio and Sterzi (2013), Picci (2010), Maggioni et al. (2007), Hoekman et al. (2009) and Hoekman et al. (2010) all utilize this framework to study patent collaboration across broad patent categories. The idea is that the propensity to collaborate should be influenced negatively by physical distance, which represents the costs of tacit knowledge transfer, as well as the innovative size of each country.

I estimate the following gravity equation where the dependent variable, P_{ijt}, is the number of collaborative energy patents between countries i and j in year t:

$$E[P_{ijt}] = exp[a_i + a_j + a_t + \beta_0 + \beta_1 lnA_{it} + \beta_2 lnA_{jt} + \beta_3 lnD_{ij} + \beta_4 lnE_{ijt} + \beta_5 lnM_{ijt} + \beta_6 T_{ijt} + \beta_7 R_{ijt} + \beta_8 C_{ijt} + \beta_9 X_{ij} + \eta_{ijt}] \tag{2.1}$$

I identify collaborative patents as patents where at least one inventor resides in a different nation. 90% of the patents in the sample have inventors from only two countries. If a patent has inventors from more than two countries, each instance of collaboration is counted uniquely. For example, if a single patent contains inventor names from China, Switzerland, and the United States, a count of 1 is assigned to each country pair: China-Switzerland, China-United States, and Switzerland-United States. An alternative method of quantifying collaboration, used by Picci (2010) in a gravity model patent collaboration study, is to utilize fractional counting. This involves assigning a count of $\frac{1}{3}$ to each country in the previous example. I choose the former method, to study the bilateral nature of knowledge transfer. Since the majority of collaborations in my sample are between only two countries,"double-counting" is less of a concern.

In this specification, A indicates a set of country specific factors, such as the total number of patent applications in all technology classes in a given year and real GDP per capita. These variables are included to control for the size of innovative activities and economic wealth. As with the dependent variable, the number of collaborative energy patent counts, total patent counts are also drawn from the OECD's Regional Patent Database and include all technological classifications. GDP per capita data is from the Penn World Table.My prediction is that the probability of collaboration in environmental technologies depends on the size, in terms of wealth and innovative activity and thus I substitute these variables for the "mass" component of the gravity formula.[5] I expect that richer, more innovative countries, will be more likely to collaborate, as these variables provide a measure of absorptive capacity. I base this prediction on evidence in the larger literature that indicates that a firm or country must have a certain level of technological skill in order to successfully absorb foreign knowledge (Keller, 2004). For example, Cassiman and Veugelers (2002), who examine the effects of knowledge flows on R&D cooperation, find that firms that have higher technological capabilities are more likely to collaborate on R&D projects.

Geographic proximity, measured by the distance between the most populated cities in kilometers, is represented by D. I obtain this data from CEPPI's *GeoDist*

[5]Montobbio and Sterzi (2013), for example, use labor force size as a "mass" variable in a patent collaboration study of all technology classes. I include real GDP per capita as a "mass" measure but not the level of real GDP because it is highly correlated with the total number of patents.

Database.[6] Keller (2004) emphasizes that distance is a significant factor in technology diffusion. For example, if technology is transferred through trade in intermediate goods (Eaton and Kortum, 2002), then one would expect technology diffusion to be geographically localized due to empirical evidence that trade declines with distance (Bergstrand, 1985). In this case, the idea that some knowledge, known as tacit knowledge, is difficult to transmit via spoken or written communication may also be important when considering distance. Literature in both economics and sociology indicates that body language and active participation in the innovating activity, that can only be achieved through person-to-person interaction, may be essential for communicating knowledge (Kim et al., 2006; MacKenzie and Spinardi, 1995). Due to this "tacitness" of knowledge transfer, I expect distance to negatively affect research collaboration.

A contribution of this paper is the inclusion of two additional variables of interest, country-level energy prices and government spending on R&D related to renewable energy which are included in E. Based on data availability for this particular time period, I am able to include natural gas prices as a measure of country-level energy prices. Natural gas is a major fuel source used in the production of electricity (IEA, 2013a). These prices are obtained from the International Energy Agency's (IEA) *Energy Prices and Taxes Statistics* and are quoted in U.S. dollars per unit.[7] The idea is that when the prices of these "dirty" inputs increase, countries will invest in the development of technologies that use less of these inputs, leading to more collaboration to aid in the development of alternative energy sources. I lag these prices by one period, as the effect of input prices is unlikely to be instantaneous. Thus, I expect energy prices to positively impact collaboration. Data related to government spending on renewable energy R&D comes from the IEA's *Energy Technology RD&D Statistics*. I expect this variable to negatively impact collaboration, as coun-

[6]See Mayer and Zignago (2011) for more information.
[7]Units of measurement for natural gas is MWh.

tries that have domestic resources to invest in the development of renewable energy sources are less likely to need international collaboration.

It is important to note that, in contrast to gravity models in the international trade literature, the dependent variable is a non directed measure. In other words, I cannot directly observe the direction in which knowledge flows. Collaborative patents do not provide information regarding the contribution of each inventor. If this were the case, countries i and j could be classified in terms of a *main* innovator and innovating partner country, providing some insight on the direction of knowledge transfer. To allow for interpretation, the variables included in E are constructed as the sum of R&D expenditures and the sum of energy prices by countries i and j.

The extensive literature on trade as a mechanism of technology diffusion motivates the inclusion of M, which represents the dollar value of country i's imports from country j, as in Montobbio and Sterzi (2013). Import data is drawn from the OECD's *STAN Bilateral Trade Database*.[8]

T is the technological similarity between countries i and j in year t. This value is measured as the angular separation, or uncentered correlation coefficient, of each country pair's vectors of patents across 8 technology classifications at time t.[9] Following Jaffe (1986) and Montobbio and Sterzi (2013), the formula for this similarity measure is given by:

$$T_{ijt} = P_{it}P'_{jt}/[(P_{it}P'_{it})(P_{jt}P'_{jt})]^{1/2} \tag{2.2}$$

Where P_{it} and P_{jt} are the two countries' vectors of patents across all classifications. The value of this coefficient ranges from zero to one, with one indicating identical distributions of technological activities (perfectly similar) and zero indicating perfect technological dissimilarity (no similarity). Countries that are more similar technologically may be better able to form synergetic relationships. Thus it is expected to

[8]Considering the value of country j's imports from country i provides similar results as the assignment of countries to i and j is random. Analyzing the value of exports also does not qualitatively change the results.

[9]This includes all categories of renewable and alternative energy used in this study.

have a positive impact on collaboration.

My unique contribution to the use of the gravity model on collaborative patenting involves the construction of a variable that measures the similarity of environmental regulations between each country pair. This variable, R, is calculated from country-level data on the percentage of tax revenue raised through environmentally related taxes relative to GDP. This data is drawn from the OECD's *Database on Instruments Used for Environmental Policy and Natural Resources Management.* Although this variable restricts the time dimension of the sample to 1994-2008, it includes data from several developing countries included in my study, notably Brazil, China, Hungary, Mexico, South Africa, and Turkey. I utilize a weighted form of the Manhattan distance formula, called the Canberra similarity measure, to quantify the similarity in regulations between two countries (Lance and Williams, 1966). The formula is given by:

$$R_{ijt} = |Tax_{it} - Tax_{jt}| \, / \, |Tax_{it} + Tax_{jt}| \tag{2.3}$$

Where Tax_{it} and Tax_{jt} are the two countries' total tax revenues raised through environmentally related taxes relative to GDP for time t. The Canberra similarity measure is more appropriate in this case because, unlike the angular separation used to measure technological similarity, it does not require two or more vectors for computation. The value of this variable also ranges from zero to one, with one indicating perfect regulation similarity and zero indicating perfect regulation dissimilarity. Countries that have similar regulatory environments are expected to collaborate more due to institutional synergies.

I also include the total number of bilateral collaborations in all technology fields between each country pair in a given year. This variable is constructed in the same way as the dependent variable, as counts of patents whose inventors come from different countries, denoted as C in Equation 2.1. I expect this variable to have a positive impact on energy patent collaboration, as it indicates an established research relationship. It may also help control for any country-pair specific variables, such as policy and trade agreements.

X is a set of time invariant dummy variables including indicators for common language and past colonial relationships. These variables are taken from the CEPPI database, and are often included in gravity model studies that relate to both trade and technological collaboration. Countries that share a common language or have ever had a colonial relationship may have reduced costs of communication. This may contribute positively to both trade and collaboration relationships. The estimating equation also includes a full set of country and time fixed effects (a_i, a_j, a_t). Summary statistics for all variables across countries and over time are included in Table A1 in the appendix.

2.3.1 Estimation strategy

While OLS is generally used to estimate log-linear gravity models, I employ an alternative econometric technique to estimate equation 2.1. The Poisson pseudo-maximum likelihood (PPML) estimator is advantageous in this context for two reasons. First, the dependent variable is a non-negative, integer count variable, for which Poisson models are commonly employed (Cameron and Miller, 2013). Second, there are many observations where collaborative environmental patenting does not take place. In other words, the dependent variable contains a significant number of zero values, 92%, here. In a traditional bilateral trade model that contains zero-trade flows, common approaches include dropping observations with zero trade, since the logarithm of zero is undefined, or adding a small value (usually 1) to zero values before taking logarithms (Bacchetta et al., 2012). The Poisson estimator is useful because it naturally accomodates zero values (Shepherd, 2013). The PPML estimator, in particular, is important in this study because it is generally consistent even when the number of zeros in the sample is quite large (Santos Silva and Tenreyro, 2011). When using PPML, the dependent variable is in levels rather than logarithmic form, however, the independent variables in logarithmic form can still be intepreted as elasticities (Silva and Tenreyro, 2006; Shepherd, 2013).

A zero inflated Poisson or negative binomial model could be used as an alternative specification. Zero inflated models assume that the dependent variable consists of two groups. In the first group, the conventional Poisson or negative binomial successfully models the process and the count can take on a positive value or a value of zero. In the second group, it is impossible to have a value other than zero and any variation in covariate values will not affect the outcome. A zero inflated model includes a logistic regression to predict which group an observation belongs to (Allison, 2012). This model is less appropriate in the case of patent collaboration because it is difficult to envision a group of country pairs where collaboration is entirely impossible. A standard panel negative binomial model, which corrects for the overdispersion caused by the large percentage of zeros, yields nearly identical results to the PPML estimates presented in the next section.

2.4 Results

2.4.1 Full sample

Table 2.4 presents the baseline Poisson pseudo-maximum likelihood (PPML) estimates. In each column, the dependent variable is the number of renewable and alternative energy collaborative patents. All explanatory variables, with the exception of technological similarity, common language, and colonial relationship are in natural logs. I include indicator variables for countries i and j to control for unobserved factors that may affect collaboration, as well as a full set of time dummies. As a benchmark parsimonious gravity model, column (1) considers only distance and mass, captured by GDP per capita and the total number of patents. Distance, both technological and physical, have a significant impact on the propensity to collaboratively patent. As expected, physical distance has a negative impact, suggesting that geographical constraints may present barriers to communication and tacit knowledge transfer. Technological similarity is positive and highly significant. This indicates that countries that are similar in terms of innovation across different energy sectors are more likely to collaborate. The coefficients on total patents, for both countries in the innovating pair, are positive and significant, illustrating the importance of absorptive capacity in collaborative relationships. The coefficient on total collaborations between country i and country j is also positive and statistically significant, indicating a positive effect of current research collaboration in all technology fields. GDP per capita does not have a significant effect.

Column (2) adds imports to the original specification. After controlling for trade, the pure effect of distance disappears completely. This may indicate that this specification captures both the direct and indirect effect (through trade relationships) of geography. Montobbio and Sterzi (2013) find that the coefficients of distance *and* trade become insignificant once import value is included in their general patent collaboration study. In my study, however, the coefficient of import value in specifications (2), (3) and (4) is positive and significant, illustrating that as the value of imports by country i from country j increases, the higher is the probability of research collaboration in energy technologies. The impact of trade is also quantitatively substantial, indicating that a 1% increase in imports is associated with a 49% increase in collaborative energy patenting in column (3), holding all other variables constant. Common language and colonial relationships are included separately in columns (3) and (4) due to their small, but positive relationship (correlation coefficient of 0.32). In line with both Montobbio and Sterzi (2013) and Picci (2010), who look at general patenting, sharing a common language facilitates collaboration as does having a past colonial relationship. Interestingly, the coefficient on the total collaborations between countries i and j is not significant in column (3). It is likely that total collaborations incorporates the effect of common langauge as a country-pair specific variable.

To explore the impact of environmental policy on the propensity to collaborate on energy patents, I present specifications that include environmental regulations, government R&D related to renewable energy, and energy prices in Table 2.5. Evidence from both the empirical and theoretical IO literature on R&D collaboration emphasize similarity as an important partner characteristic for forming compatible relationships (Veugelers, 1998). Thus, I include the measure of environmental regulation similarity in Column (1). The positive and statistically significant coefficient indicates that countries that have similar environmental regulations are more likely to collaborate on environmental technologies. The magnitude of this estimate is larger than the positive and significant impact of technological similarity. This suggests that environmental regulation similarity may be an important factor when it comes to research collaborations in energy technologies.[10] As in the baseline regression, common language has a positive and significant impact on energy patent collaboration while total collaborations between countries i and j remain insignificant.

Column (2) introduces the effect of government spending on R&D related to renewable energy. The negative coefficient of government renewable energy R&D suggests that the more countries i and j jointly spend on R&D, the less likely it is that they will collaborate on energy patents. It may be the case that countries that invest in renewable energy R&D are less likely to collaborate because they already have greater access to resources, however, this effect appears to be smaller, with an elasticity of 12%, than the other factors that positively impact collaboration.

[10]There may be some concern that collaboration with the United States may be fundamentally different. For example, countries within the European Union are subject to similar environmental policy and thus should be considered separately from the U.S. Removing the U.S. from the sample, however, does not qualitatively change the results.

Column (3) explores the role of energy prices. I include the sum of the lagged prices of natural gas for countries i and j. This coefficient is negative but lacks any explanatory power.[11]

2.4.2 Advanced and developing country matched sample

In order to explore the data in greater detail, I allow countries i and j to represent advanced and developing nations respectively. To avoid confusion with the previous analysis, I denote the advanced country as a and the developing country as d. This allows me to study how collaboration could facilitate the transfer of renewable and alternative energy technologies to the developing world. One advantage of this specification is that the tax revenue from environmental regulations variable can be included individually for each country in the innovating pair, rather than as the similarity measure R_ijt.

These specifications are presented in Table 2.6. Because energy price data for developing countries is not available, I include data on the production per capita of natural gas, measured in quadrillion btu per person, from the U.S. Energy Information Administration. Popp et al. (2011), argue that countries that have more domestic resources are more likely to have lower energy prices and thus will be less concerned with investment in renewable technologies. In this sample, no country pairs have common languages or colonial relationships. Consequently, these indicator variables are excluded. Similar reasoning is used to exclude the government renewable energy R&D variable, as few developing countries make this type of investment.

These results highlight several important points. First, the coefficient of technological similarity is a positive and significant determinant of environmental collaboration between advanced and developing countries in all specifications. Second,

[11] Including world prices of natural gas and oil produces similar results. Excluding the R&D variable and regulation similarity measure does not significantly impact the energy price coefficient.

the coefficient on total patents for the advanced country is positive and significant in Columns (1), (2), and (3), however the coefficient on total patents for the developing country is not. This may suggest that the technological capability of the advanced country is the important factor for research collaboration on energy technology. Third, the coefficient on natural gas production per capita is positive and statistically significant in Columns (3) and (4), but only for the developing country. This means that higher production per capita of natural gas in developing countries *increases* the probability of collaboration on energy patents with advanced economies. While a negative coefficient is expected for this variable, it may be the case that as developing countries produce more natural gas, they demand greater access to efficiency improving technologies. It may be difficult to distinguish between renewable and alternative energy and efficiency improving natural gas technologies from patent IPC codes alone. For example, Lanzi et al. (2011) identify energy technology patents that improve the efficiency of fossil fuels for electricity generation. In particular, one IPC code that they select is "F02C," which broadly represents gas-turbine plants as a type of general fossil fuel technology. My sample includes the IPC code "F02C 1/05," a subcategory of the IPC code identified in Lanzi et al. (2011), which identifies technologies related to gas turbine power plants using solar heat sources. Natural gas turbines are often used in conjunction with solar and wind technologies because they are intermittent sources of electricity that require backup power to meet the needs of energy intensive societies (Dodge, 2013). U.S. multinational GE recently developed a new energy efficient gas turbine that is expected to help integrate more renewable energy sources in the U.S., Europe, China, Japan, and nations in the Middle East (Bullis, 2012). In other words, developing countries who have more domestic natural gas resources may have a stronger interest in developing technologies that utilize this input more efficiently for use with renewable energy. Patents selected using the IPC codes in Tables A4 and A3 may illustrate this effect. It should be noted that this result is unique to natural gas, as including oil production per capita does not have a significant impact on energy collaboration. Thus, it is unlikely that the IPC codes used in this paper identify only "dirty" technologies. This result may illustrate the importance of natural gas for the employment of renewable energy technology.

Lastly, the coefficient on environmental tax revenue is positive and significant for the advanced country in Column (4). This may suggest that concerns over transboundary pollution may encourage countries that have strong environmental regulations to begin collaborative research projects with those that have weak environmental regulations. Distance and imports do not appear to have a significant impact on energy patent collaboration between advanced and developing countries.

2.5 Conclusion

Patent collaboration in energy technologies has the potential to reduce costs and promote the diffusion of cleaner technologies. In this paper I examine where these collaborations arise and why, to better understand the factors that may facilitate the transfer of renewable and alternative energy technology. I construct a novel country-level patent database and include energy prices and production, government renewable R&D spending, and differences in environmental regulations. This work is the first to explore the effect of these variables on collaboration in energy patenting.

The empirical results indicate that, in line with prior patent collaboration studies, technological similarity, trade relationships, innovative size, and common languages are positive predictors of collaboration in energy technologies. I find that nations that have similar environmental regulations are more likely to participate in patent collaboration, suggesting that institutional synergy may be an important motivating factor. While most patent collaborations in renewable and alternative

Table 2.4: PPML estimates for all country pairs

	(1)	(2)	(3)	(4)
Dependent variable	Collaborative patents	Collaborative patents	Collaborative patents	Collaborative patents
Distance	-0.320***	0.120	0.119	0.0693
	(0.0562)	(0.100)	(0.0888)	(0.0842)
Technological similarity	1.291***	1.107***	1.141***	1.073***
	(0.374)	(0.336)	(0.339)	(0.341)
Total patents$_i$	0.800***	0.717***	0.702***	0.695***
	(0.234)	(0.232)	(0.228)	(0.227)
Total patents$_j$	0.592***	0.430**	0.426**	0.370**
	(0.184)	(0.179)	(0.181)	(0.180)
GDP per capita$_i$	0.440	0.461	0.457	0.418
	(0.671)	(0.650)	(0.644)	(0.646)
GDP per capita$_j$	-0.522	-0.842	-0.892	-0.863
	(0.924)	(0.906)	(0.923)	(0.903)
Import value		0.561***	0.489***	0.548***
		(0.0958)	(0.0930)	(0.0871)
Common language			0.351***	
			(0.112)	
Colonial relationship				0.395***
				(0.103)
Collaborations$_{ij}$	0.103***	0.0618**	0.0418	0.0578**
	(0.0312)	(0.0283)	(0.0280)	(0.0283)
Constant	-7.236	-8.723	-7.745	-6.910
	(12.47)	(12.01)	(12.11)	(12.01)
Time dummies	Yes	Yes	Yes	Yes
Country$_i$ dummy	Yes	Yes	Yes	Yes
Country$_j$ dummy	Yes	Yes	Yes	Yes
Observations	2,284	2,284	2,284	2,284
Log pseudo-likelihood	-1497	-1459	-1452	-1450

Standard errors clustered at the country-pair level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.5: PPML estimates for all country pairs which include environmental explanatory variables

	(1)	(2)	(3)
Dependent variable	Collaborative patents	Collaborative patents	Collaborative patents
Distance	0.0834	0.0771	0.0737
	(0.0757)	(0.0748)	(0.0763)
Technological similarity	1.134***	1.112***	1.132***
	(0.333)	(0.325)	(0.323)
Total patents$_i$	0.697***	0.726***	0.715***
	(0.228)	(0.226)	(0.223)
Total patents$_j$	0.453**	0.598***	0.608***
	(0.184)	(0.193)	(0.194)
GDP per capita$_i$	0.660	0.787	0.734
	(0.650)	(0.647)	(0.650)
GDP per capita$_j$	-1.059	-0.492	-0.441
	(0.924)	(0.922)	(0.927)
Import value	0.581***	0.580***	0.571***
	(0.0910)	(0.0907)	(0.0903)
Common language	0.247**	0.259**	0.258**
	(0.112)	(0.111)	(0.111)
Collaborations$_{ij}$	0.0423	0.0320	0.0388
	(0.0275)	(0.0279)	(0.0273)
Environmental regulation similarity	1.461***	1.567***	1.533***
	(0.419)	(0.421)	(0.421)
Government renewable R&D		-0.118**	-0.112**
		(0.0568)	(0.0562)
Lag natural gas price			-0.130
			(0.142)
Constant	-8.424	-16.42	-15.88
	(12.25)	(12.34)	(12.28)
Time dummies	Yes	Yes	Yes
Country$_i$ dummy	Yes	Yes	Yes
Country$_j$ dummy	Yes	Yes	Yes
Observations	2,284	2,284	2,284
Log pseudo-likelihood	-1444	-1441	-1441

Standard errors clustered at the country-pair level in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2.6: PPML estimates for advanced and developing country pairs

	(1)	(2)	(3)	(4)
Dependent variable	Collaborative patents	Collaborative patents patents	Collaborative patents	Collaborative patents
Distance	-0.133	-0.00781	0.0962	0.104
	(0.156)	(0.261)	(0.279)	(0.270)
Technological similarity	1.501*	1.509*	1.581**	1.611**
	(0.789)	(0.793)	(0.788)	(0.793)
Total patents$_a$	0.920**	0.873**	0.986*	0.762
	(0.429)	(0.428)	(0.504)	(0.533)
Total patents$_d$	0.631	0.630	0.0827	0.0869
	(0.720)	(0.725)	(0.756)	(0.757)
GDP per capita$_a$	-2.427	-2.426	-2.859	-2.222
	(2.892)	(2.957)	(2.537)	(2.260)
GDP per capita$_d$	-0.685	-0.788	-0.526	-0.518
	(2.052)	(2.057)	(1.926)	(1.947)
Import value		0.100	0.186	0.190
		(0.146)	(0.162)	(0.155)
Collaborations$_{ad}$	0.0855	0.0828	0.0794	0.0587
	(0.206)	(0.203)	(0.203)	(0.216)
Natural gas production per capita$_a$			0.239	0.101
			(0.199)	(0.222)
Natural gas production per capita$_d$			1.232**	1.233**
			(0.510)	(0.541)
Environmental tax revenue$_a$				0.0110**
				(0.00554)
Environmental tax revenue$_d$				0.000115
				(0.00216)
Constant	15.79	15.34	28.69	20.04
	(30.59)	(30.89)	(27.31)	(26.50)
Time dummies	Yes	Yes	Yes	Yes
Country$_a$ dummy	Yes	Yes	Yes	Yes
Country$_d$ dummy	Yes	Yes	Yes	Yes
Observations	1,561	1,561	1,561	1,561
Log pseudo-likelihood	-312.3	-312.2	-310.2	-308.8

Standard errors clustered at the country-pair level in parentheses
a denotes the advanced economy and d denotes the developing country
*** p<0.01, ** p<0.05, * p<0.1

energy technologies occur between developed nations, I find that, when looking only at collaboration between advanced and developing countries, technological similarity continues to play a strong role. Higher production of natural gas positively affects the probability of collaboration for developing countries, illustrating the possibility of greater demand for efficiency improving technologies. Stronger environmental regulations in advanced nations may improve energy patent collaboration with the developing world due to concerns over global pollution levels. I also find that physical distance proves to be consistently unimportant. Due to the decline in communication and travel costs, this result is not unexpected. There is also some confirmation of this finding in the larger literature. For example, in a patent citation study, Griffith et al. (2007) find that geographic concentration of knowledge spillovers has declined significantly over time. Thus, the gravity model for energy patent collaboration hinges on innovative size and technological distance (similarity), rather than on physical proximity.

The results of this paper have strong policy implications. The International Energy Agency recommends the expansion of international collaboration on energy R&D to reduce costs and improve the efficiency of energy R&D investments (IEA, 2013b). The results of this paper suggest that this goal may be accomplished through domestic regulatory changes. Increasing the strength of environmental regulations at home could spur joint research projects abroad, to help mitigate the effects of transboundary pollution. Because technological similarity is especially important for technology transfer to the developing world, policies that help build the technological infrastructure of these nations could establish a foundation for research collaboration. Subsidies that reduce the dependency of these countries on fossil fuels may also be effective.

Chapter 3

International financial openness and industrial R&D

3.1 Introduction

The importance of financing for research and development (R&D), as a channel by which finance affects economic growth, has received recent attention in the literature (Hall and Helmers, 2010). Less work has been done on the significance of international capital markets as a source of R&D financing. One exception is work by Maskus et al. (2012) who indicate that among several measures of international financial development, only FDI is a significant factor in financing R&D. The goal of this paper is to further investigate this finding to provide a more comprehensive understanding of the effect of international financing on industrial R&D intensities.

Specifically, we examine the impact of refined measures of international financial development on R&D intensities in 22 manufacturing industries in 18 OECD countries for the period 1990-2003. We contribute by examining separately the effects of external assets and liabilities using measures of portfolio equity, FDI equity, and foreign debt. We provide additional contributions by considering the effects of financial openness as measured by capital control indices, as well as the composition and relative importance of financial intermediaries and markets across countries.

Our study relates to three broad lines of literature. First, our work relates to studies that emphasize the importance of financing for innovation. Aghion et al. (2004) and Hall and Helmers (2010) provide evidence that firms rely upon external financing from banks and equity markets to fund R&D expenditures once internal funds have been exhausted. At the industry level, Maskus et al. (2012) find several measures of domestic financial development to be significant determinants of R&D when interacted with external dependence and asset tangibility. They find that only one international channel, FDI, has a significant impact on R&D intensities. In this paper, we further consider how access to international financing may influence R&D intensities at the industry level. Second, we draw upon recent evidence that links financial openness to economic growth. Végh (2013) discusses the effectiveness of capitol controls by considering their ability to limit capitol inflows and shift the composition of flows towards long-term flows. Kose et al. (2009) provide a comprehensive overview of the influence of capitol controls on growth. They emphasize that equity market liberalization can boost growth, however, the distinction between *de facto* and *de jure* capital account openness measures can be very important. This motivates the inclusion of *de facto* and *de jure* measures of financial openness as determinants of industrial R&D, a channel that may improve economic growth. Third, our work relates to literature on financial structure. Demirguc-Kunt et al. (2011) find that financial markets become relatively more important than banks as countries develop. We consider how the relative importance of stock markets and banks may influence industrial R&D intensities.

Our results can be summarized by the following. We find that multiple capital openness indices and financial structure measures are important determinants of R&D intensity. Our results indicate that the significance of FDI as an international financial development measure is driven primarily by external assets. Specifically, industries with higher external financing needs in countries with greater FDI abroad tend to have higher R&D intensities. This suggests that multinational firms are able to access funds from affiliate firms abroad and use such funds as an important source of financing R&D expenditures.

The rest of this paper is organized as follows. Section 2 describes the methodology while section 3 describes the data used. We present our empirical results in section 4 and concluding remarks in section 5.

3.2 Methodology

We study the impact of international financial development on industrial R&D intensities, conditional on two industry characteristics identified by Maskus et al. (2012): dependence on external financing and asset tangibility. The basic idea is that industries that are more dependent on external financing will innovate more in countries that are more financially developed. International financial development should be less important for industries that have more tangible assets because they have greater access to credit due to higher levels of collateral. Maskus et al. (2012) focus on a range of measures of domestic financial development and international financial openness measures. They show that international financial openness as measured by FDI assets and liabilities is an important determinant of R&D at the industry level.

In this paper, we further explore the role of international financial openness in two ways. First, we consider the detailed channels by which international financial openness may affect R&D. Maskus et al. (2012) find FDI to be the only significant measure of international financial development to affect industrial R&D intensities. Their measure of FDI is given by the sum of external FDI assets and liabilities. We consider whether external assets or liabilities drive this result within portfolio equity, FDI equity, and foreign debt. We expect that external *liabilities*, which represent international borrowing or capital inflows to drive these results. However, given that multinationals may access funds from affiliates abroad, external assets may also be an important factor. Second, we look at a range of alternative measures of openness. These measures include indices that measure cross-border financial restrictions and the degree of financial account openness. Generally, we expect that industries that are more dependent on external financing to innovate less in countries that have more cross border financial restrictions. In other words, industries that are dependent on external financing will have fewer opportunities to access funds from abroad in countries with more capital restrictions. Similarly, we expect that industries with more tangible assets to innovate relatively more in less financially open countries as they are less likely to need international funds. In the last part of our analysis, we look at various measures of domestic financial structure to determine whether the relative importance of intermediary versus market financing can impact R&D intensities across countries. As countries grow, they tend to have larger and more active financial markets that rely more on equity relative to debt (Demirgüç-Kunt and Levine, 1996). We expect that better developed equity markets relative to debt markets can be beneficial for R&D in industries that rely more on external financing.

To test our hypotheses, we use the estimating equation from Maskus et al. (2012). This approach, developed by Rajan and Zingales (1998), includes interaction terms to allow for the utilization of cross-country variation to examine within-country differences across industries. The estimating equation is given by the following:

$$\begin{aligned}\text{R\&D intensity}_{j,k,t} =& \beta_0 + \beta_1(\text{external financial dependence}_k \text{ x financial openness}_{j,t}) \\ &+ \beta_2(\text{tangibility}_k \text{ x financial openness}_{j,t}) + \beta_3(\text{industry share}_{j,k,t}) \\ &+ \beta_4(\text{financial openness}_{j,t}) + \eta_j + \eta_k + \eta_t + \epsilon_{j,k,t}\end{aligned} \tag{3.1}$$

where j indicates countries, k denotes industries, and t represents time. The indicators η_k, η_j, and η_t control for unobserved industry, country, and time-specific effects. As in Maskus et al. (2012), we calculate R&D intensities as total industry R&D expenditures relative to industry output, across countries and time. Industry share in GDP is included to control for different industry patterns across countries.

The direct effect of financial openness is included in the regression as it varies across both countries and time. However, the direct effects of the industry characteristics are captured within η_k and are not included as separate variables since they are calculated using U.S. data and do not vary across countries or time. The two industry characteristics, external financial dependence and tangibility, are each interacted with measures of international financial openness. These two interaction terms are our primary focus. We expect β_1 to be positive and β_2 to be negative.

3.3 Data

We utilize the database constructed by Maskus et al. (2012), which includes R&D intensities for 22 manufacturing industries in 18 OECD countries from 1990-2003. R&D intensity is calculated at the industry-level as R&D expenditures as a percentage of industry production in each country.[1] Industry shares are calculated as industry production divided by GDP using data from the World Bank's *World Development Indicators 2007*.

The industry characteristics of interest include external financial dependence and tangibility. The measure of external financial dependence is from Klapper et al. (2006) and is defined as the industry-level median across firms of the ratio of capital expenditures less cash flow from operations divided by capital expenditures. This measure is calculated from Standard and Poor's Compustat database for U.S. companies from 1990-1999. Tangibility, from Braun (2005), is calculated as each industry's share of physical assets in total capital stock using U.S. data from the Compustat database for the same time frame. These industry characteristics are calculated using U.S. data and do not vary across countries or time. As Maskus et al. (2012) indicate, these characteristics represent inherent technological differences across industries that can be used to create a ranking. Using U.S. data provides

[1] R&D intensity calculated as R&D expenditures relative to value added provides similar results.

a sufficient proxy as differences in these characteristics are likely to be small across countries. Table A6 provides a summary of the industry characteristics ranked by average R&D intensity. We interact these industry characteristics with country level measures of financial openness as described below.

We first show the benchmark regression on aggregate measures of international financial openness from Maskus et al. (2012). The now standard measure of financial openness is given by the sum of external assets and liabilities, relative to GDP, analogous to trade openness as measured by the sum of exports and imports relative to GDP. Maskus et al. (2012) show that it is the FDI component of this measure that is significantly related to R&D intensity. Thus, we first show their basic results for FDI, portfolio equity, and foreign debt measured by the sum of assets and liabilities within these measures. We then consider the following refined measures of financial openness from Lane and Milesi-Ferretti (2007) in order to pick up the direction of capital flows: portfolio equity assets, portfolio equity liabilities, FDI equity assets, FDI equity liabilities, portfolio debt assets, and portfolio debt liabilities.[2] These disaggregated international financial openness measures consider the effect of the accumulated capital flows in a specific direction (i.e. inflows as captured by external liabilities and outflows as captured by external assets). These measures can be seen as *de facto* measures of international financial openness.

As an alternative measure of international financial openness, we include indices that measure *de jure* restrictions on cross-border financial transactions from Chinn and Ito (2008) and Schindler (2009). The index developed by Chinn and Ito (2008), KAOPEN, measures a country's degree of financial account openness. The indices from Schindler (2009) are based on underlying binary responses where 0 indicates unrestricted and 1 indicates restricted capital flows. The overall index is broken down into both inflow and outflow restrictions, which we include in our analysis.

[2] Total assets, total liabilities, foreign debt assets, foreign debt liabilities, other investment assets and other investment liabilities do not yield significant results.

Both the Chinn and Ito (2008) and Schindler (2009) measures allow us to explore the role of capital controls on R&D intensities.

To examine the effect of financial structure, we utilize data from the World Bank's *Financial Development and Structure Dataset 2013*. We consider three relative measures: stock market capitalization/private credit, stock market capitalization/deposit money bank assets, and stock market value traded/private credit.

3.4 Results

3.4.1 De facto measures

Table 3.1 presents the original results from Maskus et al. (2012). As these results show, FDI appears to be the only international financial development measure that significantly impacts R&D intensities. Table 3.2 presents our baseline specification using refined measures of portfolio equity, FDI equity, and portfolio debt. Each of these measures, broken down by assets and liabilities, is interacted with external financial dependence and tangibility. The results illustrate a positive and significant coefficient on the interaction of external dependence and international financial development (β_1) for portfolio equity assets, FDI assets, and portfolio debt liabilities. The coefficient of the interaction between tangibility and international financial development (β_2) is negative, but only significant for FDI assets.

The positive β_1 coefficient suggests that the original FDI estimation, using the sum of external FDI assets and liabilities, from Maskus et al. (2012) is driven by FDI assets, rather than FDI liabilities. This implies that industries that need more external financing in countries that conduct more FDI abroad may improve that country's industry level R&D. This may be due to the fact that multinational firms are already significantly innovative or it may indicate that global corporations are able to tap into funds from foreign affiliate firms. The negative β_2 coefficient sug-

Table 3.1: Regression of R&D intensity on international financial development interacted with external financial dependence and tangibility from Maskus et al. (2012)

	Total external assets and liabilities	Portfolio equity	FDI equity	Foreign debt
Industry share in GDP	-0.140***	-0.138***	-0.150***	-0.130***
	(0.0232)	(0.0241)	(0.0223)	(0.0214)
Total external assets and liabilities	-0.000359			
	(0.000617)			
External dependence*Total external assets and liabilities	0.00124*			
	(0.000729)			
Tangibility*Total external assets and liabilities	-0.000788			
	(0.00189)			
Portfolio equity		-0.000225		
		(0.00254)		
External dependence*Portfolio equity		0.00369		
		(0.00301)		
Tangibility*Portfolio equity		-0.00300		
		(0.00867)		
FDI equity			-0.00235	
			(0.00462)	
External dependence*FDI equity			0.0194***	
			(0.00521)	
Tangibility*FDI equity			-0.0191*	
			(0.0115)	
Foreign debt				-0.000871
				(0.000803)
External dependence*Foreign debt				0.000582
				(0.000926)
Tangibility*Foreign debt				0.00110
				(0.00224)
Constant	1.739***	1.684***	1.995***	1.583***
	(0.348)	(0.352)	(0.343)	(0.332)
Country-, industry- and year-dummies	Yes	Yes	Yes	Yes
Observations	3,795	3,795	3,795	3,795
Adjusted R-squared	0.464	0.463	0.469	0.463

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

gests that industries with less tangible assets benefit from being in a country with greater FDI abroad. Finally, the positive and significant β_1 coefficient on portfolio debt liabilities interacted with external financing indicates the importance of foreign borrowing (capital inflows). This may imply that the ability to borrow abroad is loosening credit constraints for firms in these industries. It is interesting that the tangibility measure interacted with debt liabilities is not significant such that industries with more tangible assets neither benefit from nor are hurt by greater access to debt liabilities.

We employ a similar thought experiment that is used in Maskus et al. (2012) and Rajan and Zingales (1998) to provide insight on the economic significance of these coefficients. We consider how much the R&D intensity of the industry at the 75th percentile of external financial dependence (furniture; manufacturing n.e.c.) exceeds

Table 3.2: Regression of R&D intensity on disaggregated measures of international financial openness interacted with external financial dependence and tangibility

	Portfolio Equity Assets	Portfolio Equity Liabilities	FDI Equity Assets	FDI Equity Liabilities	Portfolio Debt Assets	Portfolio Debt Liabilities
Industry share in GDP	-0.147***	-0.132***	-0.140***	-0.133***	-0.115***	-0.133***
	(0.0251)	(0.0224)	(0.0198)	(0.0227)	(0.0240)	(0.0234)
Portfolio equity assets	0.00217					
	(0.00820)					
External dependence*Portfolio equity assets	0.0162*					
	(0.00895)					
Tangibility**Portfolio equity assets	-0.0259					
	(0.0249)					
Portfolio equity liabilities		-0.00179				
		(0.00313)				
External dependence*Portfolio equity liabilities		0.00352				
		(0.00395)				
Tangibility**Portfolio equity liabilities		0.00259				
		(0.0109)				
FDI assets			-0.000612			
			(0.0118)			
External dependence*FDI equity assets			0.0493***			
			(0.0117)			
Tangibility*FDI equity assets			-0.0595**			
			(0.0279)			
FDI equity liabilities				-0.00254		
				(0.00727)		
External dependence*FDI equity liabilities				0.00470		
				(0.00759)		
Tangibility*FDI equity liabilities				-0.00348		
				(0.0190)		
Portfolio debt assets					-0.00546	
					(0.00378)	
External dependence*Portfolio debt assets					-0.000658	
					(0.00319)	
Tangibility*Portfolio debt assets					0.00935	
					(0.00788)	
Portfolio debt liabilities						-0.0200*
						(0.0119)
External dependence*Portfolio debt liabilities						0.0282***
						(0.0107)
Tangibility*Portfolio debt liabilities						0.00169
						(0.0212)
Constant	1.814***	1.603***	1.878***	1.674***	1.135***	1.709***
	(0.363)	(0.337)	(0.322)	(0.338)	(0.358)	(0.386)
Country-, industry- and year-dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,795	3,795	3,795	3,795	3,468	3,468
Adjusted R-squared	0.464	0.463	0.472	0.463	0.460	0.462

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

the R&D intensity of the industry at the 25th percentile of external financial dependence (pulp, paper and paper products) if both were moved from a less financially open country (25th percentile), to a more financial open country (75th percentile), while holding tangibility at its mean. We apply the same thought experiment to the tangibility measure by considering an industry at the 75th percentile of tangibility (Rubber and plastics products) with one at the 25th percentile of tangibility (chemicals and chemical products).

Table 3.3 summarizes the magnitude of the estimates that are significant in Table 3.2 by indicating the implied percentage-point change in R&D intensity relative to the average industry R&D intensity across countries and time. FDI equity assets have the largest impact, 26.7% of the average R&D intensity, based on the interaction with external dependence. This effect is larger than the 19.7% reported by Maskus et al. (2012) who conduct a similar thought experiment for total FDI. Though not as large, we find that external dependence interacted with portfolio debt liabilities and portfolio equity assets provide increases in R&D itensity of 16.3% and 5.78% of the mean R&D intensity respectively. The interaction with tangibility is only significant for FDI equity assets, however, the impact of -29.4% is again larger than the findings for total FDI (-17.4%) in Maskus et al. (2012).

3.4.2 De jure measures

In addition to the refined *de facto* measures of financial globalization in our baseline results, we also consider *de jure* restrictions on cross-border financial transactions. We interact the KAOPEN index from Chinn and Ito (2008) and Schindler (2009)'s financial restriction indices (for inflow, outflow, and overall restrictions) with both external dependence and tangibility in Table 3.4.

In the regression that includes the Chinn and Ito (2008) measure, KAOPEN, we observe a positive coefficient for the financial dependence interaction term and a

Table 3.3: Magnitudes of estimates

Differential in R&D intensity	FDI Equity Assets	Portfolio Debt Liabilities	Portfolio Equity Assets
External dependence	0.59	0.36	0.13
as percentage of R&D intensity	26.7	16.3	5.78
Tangibility	-0.65	-	-
as percentage of R&D intensity	-29.4	-	-

Note: The first line reports the difference in percentage points between an industry at the 75th percentile of external dependence in a country at the 75th percentile of the respective financial development and an industry at the 25th percentile of external dependence in a country at the 25th percentile of financial development. The second line relates the percentage point difference to the mean R&D intensity. The last two lines show magnitudes for the same thought experiment undertaken for asset tangibility.

negative coefficient on the tangibility interaction term. This index takes on higher values the more open the country is to cross border capital transactions. Thus, industries that are more dependent on external financing innovate more in countries that are more open to cross border capital transactions. Similarly, industries that have more tangible assets innovate less in countries that are more financially open because they are less likely to need funds from abroad.

The Schindler (2009) indices range from 0 to 1, with 1 indicating restricted capital flows. Thus, we expect β_1 to be negative and β_2 to be positive. We anticipate differences between inflow and outflow restrictions, with inflow restrictions expected to be more detrimental to R&D. The coefficients on the external dependence interaction terms, β_1, are negative and statistically significant across all Schindler (2009) indices. Other indices that consider equity and bond inflow and outflow restrictions from the Schindler (2009) dataset yield similar results, again with similar coefficients on restrictions of inflows and outflows. This indicates that industries who are more dependent on external financing innovate less in countries that have more restrictions. The coefficients on the tangibility interactions, β_2, are positive and statistically significant. Industries that have more tangible assets innovate more in countries that have more capital restrictions. There does not seem to be a significant difference between inflow and outflow restrictions, with surprisingly similar coefficients and significance levels. Further analysis in Table 3.5 indicates that the Schindler (2009) overall, inflow, and outflow restriction indices are highly correlated. Overall, our findings indicate that openness indices are important determinants of R&D intensity. More open countries tend to have higher R&D because industries that need external financing or have fewer tangible assets may be able to tap into international financial markets.

3.5 Financial structure

In this section we consider the structure of a country's domestic financial system. To measure the relative importance of equity markets to financial intermediation, we interact the following ratios with our two industry characteristics: stock market capitalization/private credit, stock market capitalization/deposit money bank assets, and stock market value traded/private credit. Table 3.6 illustrates the results. The coefficient on the interaction between external dependence and each financial structure measure is positive and statistically significant. This indicates that more developed equity markets, relative to financial intermediation, are associated with larger R&D investments in industries that are more dependent on external financing. The coefficient of the interaction between tangibility and each financial structure measure is not statistically significant, indicating that industries with more tangible assets neither benefit from nor are hurt by relative financial structure.

While these results suggest that equity markets may be important for R&D, growth in per capita income may also be a significant factor. Given that economic growth is associated with larger and more active financial markets, we attempt to disentangle this possible income effect by including log real GDP per capita

Table 3.4: Regression of R&D intensity on capital control indices interacted with external financial dependence and tangibility

	Chinn and Ito (2008) KAOPEN	Schindler (2009) Overall Restrictions Index	Schindler (2009) Overall Inflow Restrictions Index	Schindler (2009) Overall Outflow Restrictions Index
Industry share in GDP	-0.135***	-0.130***	-0.130***	-0.130***
	(0.0189)	(0.0232)	(0.0231)	(0.0232)
KAOPEN	-0.0572			
	(0.128)			
External dependence*KAOPEN	0.615***			
	(0.109)			
Tangibility*KAOPEN	-1.049***			
	(0.240)			
Overall restrictions index		-0.428		
		(0.696)		
External dependence*Overall restrictions index		-4.274***		
		(0.856)		
Tangibility*Overall restrictions index		7.659***		
		(1.561)		
Overall inflow restrictions index			-0.423	
			(0.588)	
External dependence*Overall inflow restrictions index			-3.581***	
			(0.854)	
Tangibility*Overall inflow restrictions index			6.468***	
			(1.574)	
Overall outflow restrictions index				-0.760
				(0.549)
External dependence*Overall outflow restrictions index				-3.904***
				(0.695)
Tangibility*Overall outflow restrictions index				6.846***
				(1.293)
Constant	2.096***	0.908***	0.981***	1.041***
	(0.344)	(0.339)	(0.318)	(0.313)
Country-, industry- and year-dummies	Yes	Yes	Yes	Yes
Observations	3,774	2,476	2,476	2,476
Adjusted R-squared	0.469	0.431	0.429	0.431

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3.5: Cross-correlation table for de jure measures

Variables	KAOPEN	Overall restrictions index	Overall inflow restrictions index	Overall outflow restrictions index
KAOPEN	1.000			
Overall restrictions index	-0.820	1.000		
Overall inflow restrictions index	-0.737	0.936	1.000	
Overall outflow restrictions index	-0.814	0.948	0.776	1.000

interacted with external financial dependence and tangibility. Table 3.7 provides these results. The sign and significance of the coefficients of interest remain largely unchanged. At the same time, the interaction between real GDP per capita and tangibility is positive and significant. This implies that industries that have more tangible assets have higher R&D intensities in richer countries.

3.6 Conclusion

In this paper we examine the impact of financial openness on R&D intensities in 22 manufacturing industries in 18 OECD countries for the period 1990-2003. We find an economically significant impact of FDI assets, rather than liabilities, on R&D intensities when interacted with industry external financial dependence and asset tangibility. We also find that several capital openness indices and financial structure measures have significant impacts on R&D intensity. Interestingly, the direction of capital flows are important for *de facto* measures, but when considering *de jure* openness indices the direction of restriction does not appear to change our results. In summary, we find that, for industries that are more dependent on external financing and that have less tangible assets, international financial openness can be a key factor in innovation investment.

Table 3.6: Regression of R&D intensity on financial structure interacted with external financial dependence and tangibility

	Stock Market Capitalization to Private Credit	Stock Market Capitalization to Deposit Money Bank Assets	Stock Market Value Traded to Private Credit
Industry share in GDP	-0.127***	-0.131***	-0.132***
	(0.0198)	(0.0227)	(0.0194)
Stock market cap/private credit	-0.462***		
	(0.156)		
External dependence*Stock market cap/private credit	1.129***		
	(0.280)		
Tangibility*Stock market cap/private credit	0.336		
	(0.363)		
Stock market cap/deposit money bank assets		-0.518***	
		(0.176)	
External dependence*Stock market cap/deposit money bank assets		1.251***	
		(0.317)	
Tangibility*Stock market cap/deposit money bank assets		0.446	
		(0.414)	
Stock market value traded/private credit			-0.285
			(0.242)
External dependence*Stock market value traded/private credit			0.896***
			(0.303)
Tangibility*Stock market value traded/private credit			0.333
			(0.557)
Constant	1.508***	1.581***	1.559***
	(0.330)	(0.375)	(0.329)
Country-, industry- and year-dummies	Yes	Yes	Yes
Observations	3,522	3,167	3,569
Adjusted R-squared	0.488	0.480	0.487

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Table 3.7: Regression of R&D intensity on financial structure and log GDP per capita interacted with external financial dependence and tangibility

	Stock Market Capitalization to Private Credit	Stock Market Capitalization to Deposit Money Bank Assets	Stock Market Value Traded to Private Credit
Industry share in GDP	-0.117***	-0.121***	-0.123***
	(0.0201)	(0.0235)	(0.0194)
Stock market cap/private credit	-0.326**		
	(0.159)		
External dependence*Stock market cap/private credit	1.150***		
	(0.286)		
Tangibility*Stock market cap/private credit	-0.116		
	(0.355)		
Stock market cap/deposit money bank assets		-0.360**	
		(0.182)	
External dependence*Stock market cap/deposit money bank assets		1.239***	
		(0.327)	
Tangibility*Stock market cap/deposit money bank assets		-0.0383	
		(0.408)	
Stock market value traded/private credit			-0.0501
			(0.246)
External dependence*Stock market value traded/private credit			0.954***
			(0.325)
Tangibility*Stock market value traded/private credit			-0.560
			(0.542)
Log real GDP per capita	-0.0527***	-0.0528***	-0.0509***
	(0.0177)	(0.0199)	(0.0153)
External dependence*Log real GDP per capita	-0.00343	0.00353	-0.00655
	(0.0159)	(0.0189)	(0.0159)
Tangibility*Log real GDP per capita	0.123***	0.109***	0.128***
	(0.0343)	(0.0412)	(0.0305)
Constant	53.13***	53.22***	51.46***
	(17.38)	(19.52)	(15.07)
Country-, industry- and year-dummies	Yes	Yes	Yes
Observations	3,522	3,167	3,569
Adjusted R-squared	0.490	0.481	0.488

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$

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Appendix

Table A1: Summary statistics for full sample

Variable	Mean	Std Dev	Min	Max	**N**
Collaborative energy patents	0.950	3.37	0	44	2284
Distance	7.906	1.221	4.088	9.883	2284
Import value	6.975	2.057	-3.324	12.238	2284
Technological similarity	0.67	0.328	0	1	2284
Total patents$_i$	6.451	1.544	1.07	9.392	2284
Total patents$_j$	5.924	2.331	0.288	10.225	2284
GDP per capita$_i$	10.232	0.322	9.017	11.048	2284
GDP per capita$_j$	10.08	0.49	8.984	11.048	2284
Collaborations$_{ij}$	0.164	0.573	0	713	2284
Common language	0.096	0.295	0	1	2284
Colonial relationship	0.044	0.206	0	1	2284
Environmental regulation similarity	0.192	0.144	0	0.712	2284
Government renewable R&D	4.418	2.638	-5.809	11.613	2284
Lag natural gas price	3.4	0.58	1.911	4.847	2284

Table A2: Summary statistics for matched advanced and developing country sample

Variable	Mean	Std Dev	Min	Max	N
Collaborative energy patents	0.119	0.604	0	11	1561
Distance	8.545	1.029	5.069	9.856	1561
Import value	6.428	2.072	-0.6	11.93	1561
Technological similarity	0.593	0.37	0	1	1561
Total patents$_a$	6.19	2.158	0	10.225	1561
Total patents$_d$	4.318	1.276	0.288	7.673	1561
GDP per capita$_a$	10.156	0.418	8.939	11.013	1561
GDP per capita$_d$	9.029	0.487	7.671	9.734	1561
Collaborations$_{ad}$	0.028	0.133	0	245	1561
Natural gas production gas per capita$_a$	-4.798	2.421	-12.067	-0.247	1561
Natural gas production gas per capita$_d$	-6.082	1.533	-9.093	-4.088	1561
Environmental tax revenue$_a$	241.575	90.512	0	520.987	1561
Environmental tax revenue$_d$	213.379	150.239	-156.868	542.820	1561

a denotes the advanced economy and d denotes the developing country

Table A3: Renewable Energy IPC codes from Johnstone et al. (2010)

Description	IPC code (s)
Wind	
Wind motors with rotation axis substantially in wind direction	F03D 1
Wind motors with rotation axis substantially at right angle to wind direction	F03D 3
Other wind motors	F03D 5
Controlling wind motors	F03D 7
Adaptations of wind motors for special use	F03D 9
Details, component parts, or accessories not provided for in, or of interest apart from, the other groups of this subclass	F03D 11
Solar	
Devices for producing mechanical power from solar energy	F03G 6
Use of solar heat, e.g. solar heat collectors	F24J 2
Devices consisting of a plurality of semiconductor components sensitive to infra-red radiation, light— specially adapted for the conversion of the energy of such radiation into electrical energy	H01L 27/142
Semiconductor devices sensitive to infra-red radiation, light—adapted as conversion devices	H01L 31/04-078
Generators in which light radiation is directly converted into electrical energy	H02N 6
Aspects of roofing for energy collecting devices—e.g. incl. solar panels	E04D 13/18
Geothermal	
Production or use of heat, not derived from combustion—using natural or geothermal heat	F24J 3
Devices for producing mechanical power from geothermal energy	F03G 4
Mechanical-power-producing mechanisms—using pressure differences or thermal differences occurring in nature	F03G 7/04
Ocean	
Tide or wave power plants	E02B 9/08
Submerged units incorporating electric generators or motors characterized by using wave or tide energy	F03B 13/10-26
Mechanical-power producing mechanisms—ocean thermal energy conversion	F03G 7/05
Biomass and waste	
Solid fuels essentially based on materials of non-mineral origin—animal or vegetable substances; sewage, town, or house refuse; industrial residues or waste materials	C10L 5/40-48
Engines or plants operating on gaseous fuel generated from solid fuel, e.g. wood	F02B 43/08
Liquid carbonaceous fuels; Gaseous fuels; Solid fuels	C10L 1 C10L 3
Dumping solid waste;	C10L 5
Destroying solid waste or transforming solid waste into something useful or harmless;	B09B1
Incineration of waste; Incinerator constructions;	B09B
Incinerators or other apparatus specially adapted for consuming specific waste or low grade fuels, e.g. chemicals	F23G5
Plants or engines characterized by use of industrial or other waste gases	F23G 7
Profiting from waste heat of combustion engines;	F01K 27
Machines, plant, or systems, using particular sources of energy—using waste heat, e.g. from internal-combustion engines;	F02G 5 F25B 27/02
Incineration of waste; incinerator constructions;	F23G 5
Incinerators or other apparatus specially adapted for consuming specific waste or low grade fuels, e.g. chemicals	F23G 7
Plants or engines characterized by use of industrial or other waste gases	F01K 25/14
Incineration of waste—recuperation of heat	F23G 5/46

Table A4: Alternative Energy IPC codes from the World Intellectual Property Organization (WIPO) IPC Green Inventory

Description	IPC code (s)
Bio-fuels	
Solid fuels	C10L 5/00, 5/40-5/48
Torrefaction of biomass	C10B 53/02
	C10L 5/40, 9/00
Liquid fuels	C10L 1/00, 1/02, 1/14
Vegetable oils	C10L 1/02, 1/19
Biodiesel	C07C 67/00, 69/00
	C10G
	C10L 1/02, 1/19
	C11C 3/10
	C12P 7/64
Bioethanol	C10L 1/02, 1/182
	C12N 9/24
	C12P 7/06-7/14
Biogas	C02F 3/28, 11/04
	C10L 3/00
	C12M 1/107
	C12P 5/02
From genetically engineer organisms	C12N 1/13, 1/15, 1/21, 5/10, 15/00
	A01H
Integrated gasification combined cycle (IGCC)	C10L 3/00
	F02C 3/28
Fuel cells	H01M 4/86-4/98, 8/00-8/24, 12/00-12/08
Electrodes	H01M 4/86-4/98
Inert electrodes with catalytic activity	H01M 4/86-4/98
Non-active parts	H01M 2/00-2/04 , 8/00-8/24
Within hybrid cells	H01M 12/00-12/08
Pyrolysis or gasification of biomass	C10B 53/00
	C10J
Harnessing energy from manmade waste	
Agricultural waste	C10L 5/00
Fuel from animal waste and crop residues	C10L 5/42, 5/44
Incinerators for field, garden or wood waste	F23G 7/00, 7/10
Gasification	C10J 3/02, 3/46
	F23B 90/00
	F23G 5/027
Chemical waste	B09B 3/00
	F23G 7/00
Industrial waste	C10L 5/48
	F23G 5/00, 7/00
Using top gas in blast furnaces to power pig-iron production	C21B 5/06
Pulp liquors	D21C 11/00
Anaerobic digestion of industrial waste	A62D 3/02
	C02F 11/04, 11/14
Industrial wood waste	F23G 7/00, 7/10
Hospital waste	B09B 3/00
	F23G 5/00
Landfill gas	B09B
Separation of components	B01D 53/02, 53/04, 53/047, 53/14, 53/22, 53/24
	C10L 5/46
Municipal waste	F23G 5/00

Description	IPC code (s)
Wind energy	F03D
Structural association of electric generator with mechanical driving motor	H02K 7/18
Structural aspects of wind turbines	B63B 35/00 E04H 12/00 F03D 11/04
Propulsion of vehicles using wind power	B60K 16/00
Electric propulsion of vehicles using wind Power	B60L 8/00
Propulsion of marine vessels by wind-powered motors	B63H 13/00
Solar energy	
Photovoltaics (PV)	
Devices adapted for the conversion of radiation energy into electrical energy	H01L 27/142, 31/00-31/078 H01G 9/20 H02N 6/00
Using organic materials as the active part	H01L 27/30, 51/42-51/48
Assemblies of a plurality of solar cells	H01L 25/00, 25/03, 25/16, 25/18, 31/042
Silicon; single-crystal growth	C01B 33/02 C23C 14/14, 16/24 C30B 29/06
Regulating to the maximum power available from solar cells	G05F 1/67
Electric lighting devices with, or rechargeable with, solar cells	F21L 4/00 F21S 9/03
Charging batteries	H02J 7/35
Dye-sensitised solar cells (DSSC)	H01G 9/20 H01M 14/00
Use of solar heat	F24J 2/00-2/54
For domestic hot water systems	F24D 17/00
For space heating	F24D 3/00, 5/00, 11/00, 19/00
For swimming pools	F24J 2/42
Solar updraft towers	F03D 1/04, 9/00, 11/04 F03G 6/00
For treatment of water, waste water or sludge	C02F 1/14
Gas turbine power plants using solar heat source	F02C 1/05
Hybrid solar thermal-PV systems	H01L 31/058
Propulsion of vehicles using solar power	B60K 16/00
Electric propulsion of vehicles using solar power	B60L 8/00
Producing mechanical power from solar energy	F03G 6/00-6/06
Roof covering aspects of energy collecting devices	E04D 13/00, 13/18
Steam generation using solar heat	F22B 1/00 F24J 1/00
Refrigeration or heat pump systems using solar energy	F25B 27/00
Use of solar energy for drying materials or objects	F26B 3/00, 3/28
Solar concentrators	F24J 2/06 G02B 7/183
Solar ponds	F24J 2/04

Description	IPC code (s)
Hydro energy	
Water-power plants	E02B 9/00-9/06
Tide or wave power plants	E02B 9/08
Machines or engines for liquids	F03B F03C
Using wave or tide energy	F03B 13/12-13/26
Regulating, controlling or safety means of machines or engines	F03B 15/00-15/22
Propulsion of marine vessels using energy derived from water movement	B63H 19/02, 19/04
Ocean thermal energy conversion (OTEC)	F03G 7/05
Using waste heat	
To produce mechanical energy	F01K 27/00
Of combustion engines	F01K 23/06-23/10 F01N 5/00 F02G 5/00-5/04 F25B 27/02
Of steam engine plants	F01K 17/00, 23/04
Of gas-turbine plants	F02C 6/18
As source of energy for refrigeration plants	F25B 27/02
For treatment of water, waste water or sewage	C02F 1/16
Recovery of waste heat in paper production	D21F 5/20
For steam generation by exploitation of the heat content of hot heat carriers	F22B 1/02
Recuperation of heat energy from waste incineration	F23G 5/46
Energy recovery in air conditioning	F24F 12/00
Arrangements for using waste heat from furnaces, kilns, ovens or retorts	F27D 17/00
Regenerative heat-exchange apparatus	F28D 17/00-20/00
Of gasification plants	C10J 3/86
Devices for producing mechanical power from muscle energy	F03G 5/00-5/08
Other production or use of heat, not derived from combustion, e.g. natural heat	F24J 1/00, 3/00, 3/06
Heat pumps in central heating systems using heat accumulated in storage masses	F24D 11/02
Heat pumps in other domestic- or space-heating systems	F24D 15/04
Heat pumps in domestic hot-water supply systems	F24D 17/02
Air or water heaters using heat pumps	F24H 4/00
Heat pumps	F25B 30/00
Geothermal energy	
Use of geothermal heat	F01K F24F 5/00 F24J 3/08 H02N 10/00 F25B 30/06
Production of mechanical power from geothermal energy	F03G 4/00-4/06, 7/04

Table A5: List of countries

Advanced countries		Developing countries	
Australia	AU	Brazil	BR
Austria	AT	Bulgaria	BG*
Belgium	BE*	China	CN
Canada	CA	Hungary	HU
Chile	CL	India	IN*
Czech Republic	CZ	Mexico	MX
Denmark	DK	Romania	RO*
Estonia	EE	South Africa	ZA
Finland	FI	Turkey	TR
France	FR		
Germany	DE		
Ireland	IE		
Israel	IL		
Italy	IT		
Japan	JP		
Korea	KR		
Luxembourg	LU		
Netherlands	NL		
New Zealand	NZ		
Norway	NO		
Poland	PL		
Portugal	PT		
Slovak Republic	SK		
Slovenia	SI		
Spain	ES		
Sweden	SE		
Switzerland	CH		
United Kingdom	GB		
United States	US		

*Excluded from estimations due to missing data, but included in the OECD Regional Patent Database.

Figure A1: Example collaborative patent abstract

(19) Europäisches Patentamt
European Patent Office
Office européen des brevets

(11) **EP 2 085 985 A2**

(12) **EUROPEAN PATENT APPLICATION**

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Remarks:
This application was filed on 11-08-2009 as a divisional application to the application mentioned under INID code 62.

(54) **Dye sensitized solar cell**

(57) A dye sensitized solar cell, wherein a compacting compound whose molecular structure comprises a terminal group, a hydrophobic part and an anchoring group is co-adsorbed together with the dye on the semiconductive metal oxide layer of the photoanode, forming a dense mixed self-assembled monolayer.

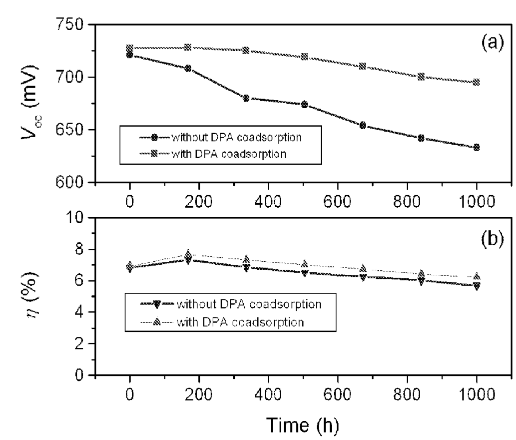

Fig. 5

EP 2 085 985 A2

Table A6: Industry characteristics ranked by average R&D intensity

Industry name	ISIC	External dependence	Tangibility	Average R&D Intensity
Radio, television and communication equipment	32	0.328	0.159	0.090
Office, accounting and computing machinery	30	0.502	0.113	0.066
Medical, precision and optical instruments	33	0.643	0.145	0.050
Other transport equipment	35	0.124	0.242	0.042
Chemicals and chemical products	24	0.791	0.178	0.040
Electrical machinery and apparatus, n.e.c.	31	0.137	0.209	0.029
Motor vehicles, trailers and semitrailers	34	0.394	0.273	0.024
Machinery and equipment, n.e.c.	29	0.076	0.209	0.019
Rubber and plastics products	25	0.300	0.364	0.014
Basic metals	27	0.147	0.410	0.007
Other nonmetallic mineral products	26	-0.121	0.389	0.006
Tobacco products	16	0.944	0.188	0.006
Furniture; manufacturing n.e.c.	36	0.376	0.184	0.005
Textiles	17	0.262	0.343	0.005
Fabricated metal products, except machinery and equipment	28	0.166	0.276	0.005
Pulp, paper and paper products	21	0.123	0.504	0.005
Coke, refined petroleum products and nuclear fuel	23	-0.044	0.611	0.005
Leather, leather products and footwear	19	0.098	0.123	0.004
Wearing apparel, dressing and dying of fur	18	0.174	0.126	0.003
Food products and beverages	15	0.181	0.347	0.002
Wood and products of wood and cork	20	0.156	0.447	0.002
Printing and publishing	22	0.096	0.214	0.001
Mean		0.266	0.275	0.020
Min		-0.121	0.113	0.001
Max		0.944	0.611	0.090

CURRICULUM VITAE

Sahar Milani

Academic Appointments

Assistant Professor, St. Lawrence University, August 2015

Education

Ph.D. Economics, University of Wisconsin - Milwaukee, 2015

M.S. Management, University of Wisconsin - Milwaukee, 2009

B.B.A. Finance, University of Wisconsin - Madison, 2007

Fields of Interest

Research: Environmental Economics, Economic Development, Macroeconomics

Teaching: Macroeconomics, Environmental Economics, Monetary Economics

Research Experience

Research Assistant, University of Wisconsin - Milwaukee, 2013 - 2014

Working Papers

"The impact of environmental policy stringency on industrial R&D conditional on pollution intensity and relocation costs"
Revise and resubmit at *Environmental and Resource Economics*

"Who innovates with whom and why? Evidence from international collaboration in energy patenting"

"International financial openness and industrial R&D"
(with Rebecca Neumann)

Teaching Experience

University of Wisconsin - Milwaukee

Financial Institutions: 2014

Money and Banking: 2013 - 2014

Analysis of U.S. Business Environment (MBA Level Macroeconomics): 2013

Principles of Macroeconomics: 2010 - 2015

Economics of Personal Finance: 2010 - 2015

Honors and Awards

Jack F. Reichert Business Scholarship, 2009

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Wisconsin Economics Association Annual Meeting, Stevens Point, WI, November 8-9, 2013

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University Service

New course development: Online UPACE format for The Economics of Personal Finance (with Rebecca Neumann), 2015

Speaker at University of Wisconsin - Milwaukee Department of Economics TA Training, 2013

Financial Literacy Instructor, University of Wisconsin - Milwaukee Student Support Services Summer Bridge Program, 2010

President, Graduate Business Association, 2009

Professional Associations

American Economic Association

Association of Environmental and Resource Economists

Midwest Economic Association

Wisconsin Economic Association

Other Skills

Software: STATA, Minitab, E-Views, GAUSS, LaTeX