1-1-2008

Federal Renewable-Energy Research And Development Funding And Innovation

Darrin B. Johnson
Eastern Illinois University

Recommended Citation

Johnson, Darrin B., "Federal Renewable-Energy Research And Development Funding And Innovation" (2008). *Masters Theses*. 200.
http://thekeep.eiu.edu/theses/200

FEDERAL RENEWABLE-ENERGY RESEARCH AND DEVELOPMENT FUNDING AND INNOVATION

JOHNSON

THESIS REPRODUCTION CERTIFICATE

TO: Graduate Degree Candidates (who have written formal theses)

SUBJECT: Permission to Reproduce Theses

The University Library is receiving a number of request from other institutions asking permission to reproduce dissertations for inclusion in their library holdings. Although no copyright laws are involved, we feel that professional courtesy demands that permission be obtained from the author before we allow these to be copied.

PLEASE SIGN ONE OF THE FOLLOWING STATEMENTS:

Booth Library of Eastern Illinois University has my permission to lend my thesis to a reputable college or university for the purpose of copying it for inclusion in that institution's library or research holdings.

Author's Signature ____________

Date 5-14-08

I respectfully request Booth Library of Eastern Illinois University **NOT** allow my thesis to be reproduced because:

____

____

____

Author's Signature ____________

Date ____________

This form must be submitted in duplicate.

Federal Renewable-Energy Research and Development Funding and Innovation

(TITLE)

BY

Darrin B Johnson

THESIS

SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF

Master of Arts in Economics

IN THE GRADUATE SCHOOL, EASTERN ILLINOIS UNIVERSITY
CHARLESTON, ILLINOIS

2008
YEAR

I HEREBY RECOMMEND THAT THIS THESIS BE ACCEPTED AS FULFILLING
THIS PART OF THE GRADUATE DEGREE CITED ABOVE

May 14, 2008
DATE

THESIS DIRECTOR

May 14, 2008
DATE

Ebrahim Karbassioon
DEPARTMENT/SCHOOL HEAD

Abstract

Energy is the largest industry on the planet and necessary for the sustainability of life. As the world's stores of nonrenewable-energy begin to deplete at an increasing rate, the research on feasible sources of renewable-energy becomes essential. The objective of this study is to evaluate the relationship between federal funding for activities of energy research and development for renewable-energy sources and the resulting number of renewable-energy patent applications. Panel and ordinary least squares estimations are applied. Data consists of nineteen countries spanning the years from 1985 through 1997. Results indicate a weak and statistically insignificant relationship between federal renewable-energy R&D and renewable-energy patent applications. Explanations for this weak relationship - including inadequate levels of federal renewable-energy R&D funding and barriers associated with the implementation of renewable-energy technologies - are considered.

Table of Contents

Listing of Tables and Figures

Introduction

As worldwide demand for energy continues to grow, the need for innovation in renewable-energy technologies grows in importance. Growing populations and economic development throughout the world intensify this need. In 1980, total world energy use was 283 quadrillion British Thermal units (BTUs) and is projected to reach 722 quadrillion BTUs by the year 2030. Oil consumption is also projected to increase from 2003 levels of 80 million barrels per day to 118 million barrels per day in 2025 (Energy Information Administration, 2006). As these trends continue, renewable-energy technologies will become necessary as a source of cost-effective and sustainable energy.

Despite the importance of renewable-energy research and development (R&D) and the recommendations of experts, energy R&D funding is declining. A 1997 report from the President's Committee of Advisors on Science and Technology and a 2004 report from the bipartisan national Commission on Energy Policy recommended doubling federal R&D funding for energy. However, the 2005 U.S. federal budget reduced energy R&D by 11% from 2004 levels and the Advancement of Science projects a further decline of 18% (Nemet and Kammen, 2007).

The focus of this study is the relationship between federal R&D funding of renewable-energy and renewable-energy innovation. Innovation is measured by patent applications. Patents, although far from perfect, are often the best indicator of innovation available (Sanyal, 2003).

Previous studies using patents as a measure of innovation include Schmookler (1966), Griliches (1989), and Griliches (1990). Schmookler's study finds a positive relationship between patents and industry investment and between patents and industry sales, both of which support the role of demand in stimulating technical change (Schmookler, 1966). The relationship between patents and R&D funding has been studied extensively. Pakes and Griliches (1980) estimates a knowledge production function that translates past R&D funding and a disturbance term into changes in patenting. Pakes and Griliches (1984) finds a strong relationship between R&D funding and the number of patents received by firms. Hall, Griliches, and Hausman (1986) finds that changes in a firm's level of investment in R&D parallels with changes in patent numbers. Similar results are also found by Bound et al. (1984), Hausman et al. (1984) and Jaffe (1986).

More recent studies have begun to utilize international data and to focus on specific sectors. For instance, Meliciani (2000) examines two of the main drivers of technological growth - R&D and investment – by testing the effectiveness of R&D and investment across sectors using data from twelve countries and fifteen industrial sectors. Margolis and Kammen (2001) focus on the energy sector and find that energy R&D expenditures and energy patents exhibit strong correlations.

The objective of this study is to evaluate the relationship between federal funding for activities of energy research and development for renewable-energy sources and the resulting number of renewable-energy patent applications. As the world's resources of nonrenewable-energy continue to decline at increasing rates, the development of renewable-energy technology becomes increasingly important. Understanding the relationship between federal R&D funding and innovation in renewable-energy technology is an important step in this process.

Literature Review

The use of patent data as a proxy for innovation has been widely used in previous studies. Schmookler (1966), Griliches (1989), and Griliches (1990) all use this approach. Schmookler's study finds a positive relationship between patents and industry investment and between patents and industry sales, both of which support the role of demand in stimulating technical change (Schmookler, 1966).

Griliches (1989) considers a broad range of issues involving patents, including the relationship between the number of patents granted and the number of resources available to the U.S. Patent Office, the crowding out effect of domestic patents by foreign patent applications, the change in growth rates of patent applications due to a change in shifts away from traditionally high-patenting areas toward lower-patenting areas, and the relationship between R&D and patents. The study concludes that fluctuations in R&D funding affect the number of patent applications but less than proportionately (Griliches, 1989).

Griliches (1990) addresses some of the problems associated with patents as a measure of technological change, such as classification and intrinsic variability, and examines the presence of diminishing returns to R&D. Pakes and Griliches (1980) estimates a knowledge production function that translates past R&D and a disturbance term into changes in patenting. Pakes and Griliches (1984) finds a strong relationship between R&D and the number of patents received by firms. Hall, Griliches, and Hausman (1986) finds that changes in a firm's level of R&D investment parallels with changes in patent numbers. Similar results are also found by Bound et al. (1984), Hausman et al. (1984) and Jaffe (1986).

More recent studies examine the R&D and innovation relationship both at an international level and for specific sectors of the economy. For instance, Evenson (2001) studies the effects of R&D funding on patent output using data for the United States, the United Kingdom, France and Germany across nine different industries. The study examines the effects of three different types of factors, including "propensity-to-patent" factors, invention-demand factors, and invention potential factors. "Propensity-to-patent" factors include factors that affect changes in the proportion of inventions actually patented, invention-demand factors include factors that affect the value of the marginal product of inventions, and invention potential factors include the relative rates of invention potential "recharge" and invention potential "exhaustion". The study finds strong support for the demand explanation, significance of the competition variables in a pooled-industry regression only, and no strong recharge effects (Evenson, 2001).

Two of the main drivers of technological growth - R&D funding and investment - are examined in Meliciani (2000) by maximizing the "...log-likelihood function of the Poisson model where the explanatory variables are R&D expenditures and investment" (Meliciani, 2000). Panel analysis consisting of twelve countries and fifteen industrial sectors over the period 1973-1993 is used. R&D funding is measured as total business expenditure on R&D and investment is measured as gross fixed capital formation. The study concludes that R&D funding and investment are positive and highly significant with elasticities of 0.18 and 0.19 respectively. R&D funding is found to be more effective in science based industries while investment is found to be more effective in supplier dominated and production intensive sectors (Meliciani, 2000).

A similar approach is used by Ulku (2004) in a study that includes a broader range of explanatory variables, including the stock of gross R&D funding, GDP, gross fixed investment, secondary school enrollments, labor population, imports and exports of manufacturing goods, openness in current prices, expropriation risk index, and the U.S. trade share. The study uses fixed-effects and Arellano-Bond GMM estimators and finds that R&D stock is positive and significant in G-7 countries, other large market OECD countries, and low-income OECD countries. Specifically, a one percent increase in per capita R&D stock increases innovation by 0.40 percent in G-7 and large market countries, and increases innovation by 0.50 percent in low-income OECD countries (Ulku, 2004). The study also concludes that countries without significant R&D sectors have significant coefficients for the import share of trade in manufacturing goods, implying that these countries import the knowledge and benefits of the R&D efforts of other countries rather the providing their own effective R&D programs.

Margolis and Kammen (2001), utilizes data on international public sector energy R&D funding, U.S. total R&D investments, and patents to explore the relationship between energy R&D funding and innovation. A major conclusion of this study is that "… in the U.S. the total number of patents and total funds for R&D have been highly correlated over the past two decades – both roughly doubled between 1976 and 1996" (Margolis and Kammen, 2001). Energy R&D funding and energy patents have also exhibited strong correlation, but rather than the upward trend seen in total R&D funding and total patents, energy R&D funding and energy patents have both declined.

A related study, Nemet and Kammen (2007), consists of an analysis of R&D investment data, development of indicators of innovative activity, and an assessment of the feasibility of expanding to much larger levels of R&D. Patents are used as a proxy for innovation and are found to be strongly correlated with R&D funding across a variety of energy technologies. The study examines specific types of energy technologies and finds that "public R&D and patenting are highly correlated for wind, PV, fuel cells, and nuclear fusion" (Nemet and Kammen, 2007).

Data and Methodology

For this study, panel and ordinary least squares estimations are used. Data consists of nineteen countries (see Table 1 for a listing of countries in the study) spanning the years 1985 to 1997. A series of models are used allowing conclusions to be made about the effectiveness of federal R&D funding on patent applications for total federal R&D, federal energy R&D, and federal renewable-energy R&D. For each type of R&D, a log-linear model is used in order to linearize the data and dampen the effects of outliers.

Figure 5 provides graphical representations of the data for each explanatory variable plotted against the dependent variable. In each case, the left hand side is a graph of the raw data and the right hand side is a graph of the log-transformed data. For many of the variables the log transformation dampens outliers and creates a linear relationship between the explanatory variable and the dependent variable. The log transformation of researchers is not used because researchers are reported as a percentage of the total labor force, and the log transformation of the openness variable is not used because it is a ratio of the sum of exports and imports to GDP per capita.

Formal tests can also be applied to determine whether a log-linear model is more appropriate than a linear model. A test proposed by MacKinnon, White, and Davidson (1983), which tests the null hypothesis that the dependent variable is a linear function of the explanatory variables and the alternative hypothesis that the logarithmic transformation of the dependent variable is a linear function of the logarithmic transformation of the explanatory variables can be used for this determination. Rather than applying the MacKinnon, White, and Davidson test, however, a Box-Cox transformation is applied.

A Box-Cox transformation is also used to determine whether a linear or log-linear model is appropriate. The Box-Cox transformation tests the null hypothesis that the linear and log-linear models are empirically equivalent. Calculations for the determination of the Box-Cox test statistic result in a value of 405.31, which is much greater that the χ^2 critical value of 3.84. Therefore, the null hypothesis is rejected, leading to the conclusion that the linear and log-linear models are not empirically equivalent. A comparison of the sum of squared residuals for the linear model divided by the square of the geometric mean, and the sum of squared residuals for the log-linear model is then made. The value for the linear model is 1184.08 and is much larger than the sum of squared residuals of the log-linear model of 23.14. This result leads to the conclusion that the log-linear model is more appropriate than the linear model.

In addition to relying on formal tests such as that proposed by MacKinnon, White, and Davidson, and the Box-Cox transformation, the decision to use a log-linear model can also be arrived at by a graphical examination of the data. Scatter plots of the dependent variable versus each individual explanatory variable for both a linear model and a log-linear model should be examined. Scatter plots for the log-linear model, shown in Figure 5, in general, indicate the existence of linear relationships whereas the scatter plots of the linear model, in general, do not. Based on the indications of the analysis of the scatter plots, and the results from the Box-Cox transformation, a log-linear model is used.

Model 1 – Total

$$ln(TPATS)_{it} = \beta_0 + \beta_1 ln(TRD)_{it} + \beta_2 ln(TRD)_{it}^2 + \beta_3(RES)_{it} + \beta_4(RES)_{it}^2 + \beta_5 ln(ARTS)_{it} + \beta_6(OPEN)_{it} + \beta_7 ln(INV)_{it} + \beta_8 ln(FDI)_{it} + \beta_9 ln(FEES)_{it} + \beta_{10} ln(GDP)_{it} + \epsilon_{it} \quad (1)$$

Model 1 examines the relationship between total federal R&D funding and total patent applications, and is estimated with panel estimation. Panel estimation considers both fixed effects and random effects. The fixed effects model has the general form of $Y_{it} = (\alpha + \mu_i) + X'_{it}B + v_{it}$, and is used to control for omitted variables that differ between cases but are not constant over time. Running a fixed effects model is equivalent to generating a dummy variable for each country and including these variables in the regression. As a result, one degree of freedom is lost for each dummy variable, and, thus, each country or group. The random effects model has the general form of $Y_{it} = \alpha + X'_{it}B + (u_i + v_{it})$. With the random effects model, uncontrolled random factors are influencing the trend of the model.

Patent applications data is available through the United States Patent and Trademark Office (USPTO). Patent applications, rather than patents granted, are used because "… inventors have a strong incentive to apply for a patent as soon as possible following the completion of the innovation whereas the grant date depends upon the review process at the USPTO, which takes on average about 2 years, with a significant variance… Thus, and whenever possible, the application date should be used as the relevant time placer for patents" (Hall, Jaffe, and Trajtenberg, 2001). Numerous additional studies support the use of patent applications rather than patent grants.

More specifically, the patent database developed by Hall, Jaffe, and Trajtenberg, consisting of nearly three million granted utility patents spanning the years 1963 through 1999, is used. Patent application data after 1997 is not used due to a sharp drop in the number of patent applications as a result of observing only those applications applied for after 1997 and granted quickly enough to be recorded in the database by 1999. Patents are classified according to year of application, country of origin, and patent class, as well as others. This makes it possible to determine not only the total number of patent applications in a given year for each country, but also the number of renewable-energy patent applications in a given year for each country.

Total federal R&D funding data is available from the Organization for Economic Cooperation and Development (OECD) Main Science and Technology Indicators and is measured as government's share of gross domestic expenditure on research and development in millions of constant 2000 U.S. dollars. The square of total federal R&D funding is also included in order to test for diminishing marginal returns to R&D.

Human capital's effect on innovation is measured as the number of full-time researchers employed as a percentage of the total labor force. Using researchers as a percentage of the labor force, rather than the raw data, makes it possible to control for the overall labor supply of a country. The square of this variable is also included in order to test for diminishing marginal returns to human capital. Researcher data is available from the OECD Main Science and Technology Indicators and labor force data is available through the World Development Indicators (WDI) database.

The existing stock of knowledge has also been shown to impact innovation. Previous studies have used a variety of different variables as a proxy for the existing stock of knowledge. For instance, Popp (2002) creates a measure of the existing stock of knowledge using patent citations and patent counts. Coe and Helpman (1995) use cumulative R&D funding as a measure of the existing stock of knowledge. This study uses the number of scientific and engineering journal articles as a proxy for the existing stock of knowledge. Scientific journal data is available from WDI and is defined as the number of scientific and engineering articles published in the areas of physics, biology, mathematics, clinical medicine, biomedical research, engineering and technology, and earth and space sciences (WDI 2005).

A country's measure of trade openness is also included in the model. Openness measures total trade (measured as the sum of exports and imports) as a percentage of GDP per capita, and is available from Penn World Tables. Including the openness variable in the model allows the effects of technology spillover to be observed. Many other measures of technology spillovers have been used in previous studies. For instance, Coe and Helpman (1995) develop a model using foreign R&D as a measure of technology spillover and concludes that foreign R&D capital stocks have important effects on total factor productivity. Additional measures of existing knowledge stock may be explored in future research.

"Technological change has not only a disembodied but also an embodied nature. Therefore the activity of investment has to be taken into account as an important source of innovation" (Meliciani, 2000). In this study, investment is measured as gross fixed capital formation (see Meliciani, 2000; Ulku, 2004) and is reported in constant 2000 U.S. dollars. Findings from Meliciani's study indicate that the acquisition of capital goods can, in some sectors, be a more important source of innovation than R&D funding. The positive influence of investment is found to be most significant for small firms and in less technologically intensive industrial sectors.

In addition to gross fixed capital formation, foreign direct investment (FDI) is also included in the model. In addition to providing resources for the acquisition of capital goods, FDI is also a measure of technology spillover. Firms investing in and establishing operations in other countries also bring technology into the country. As a result, countries with higher levels of FDI are likely to have a greater number of patent applications. Foreign direct investment data and gross fixed capital formation data are both available from WDI.

Fees associated with applying for a patent will also be included in the model. Patent fees data is available from the USPTO. There are a wide number of various fees associated with patents. For this study, the original patent application filing fee is used since every patent application is subjected to this fee. Lastly, GDP is included in the model to control for the economic size and the business cycle of each country. A detailed description of the variables used in the study is provided in Table 2.

Model 2 – Energy

$$ln(EPATS)_i = \beta_0 + \beta_1 ln(ERD)_i + \beta_2 ln(ERD)_i^2 + \beta_3 ln(RES)_i + \beta_4 ln(RES)_i^2 + \beta_5 ln(ARTS)_i + \beta_6 (OPEN)_i + \beta_7 ln(INV)_i + \beta_8 ln(FDI)_i + \beta_9 ln(FEES)_i + \beta_{10} ln(GDP)_i + \epsilon_i \quad (2)$$

Model 2 focuses on the relationship between federal energy R&D and energy patent applications. Two changes to the initial model are needed. First, energy patent applications are used rather than total patent applications. Second, federal energy R&D expenditure data is used rather than total federal R&D expenditure data. Federal energy R&D data is available from the International Energy Agency (IEA) and is measured in millions of 2005 US dollars. Federal energy R&D expenditure data includes the areas of energy efficiency, fossil fuels, renewable energy, nuclear fusion and fission, hydrogen and fuel cells, and "other power and storage technologies".

In order to construct a database of energy patent applications it is necessary to determine which USPTO patent classes are related to energy technologies. Fortunately, this has been done. Popp (2002) uses resources from the Department of Energy and academic sciences to identify areas of energy technology. These technologies are then matched with patent sub-classifications and grouped according to the specific type of technology involved. The sub-classifications used by Popp (2002) are based on the classifications of the MicroPatent CD-ROM database rather than the database created by Hall, Jaffe, and Trajtenberg (2001). As a result, some of the classifications that are possible with the MicroPatent database are not possible in the current study. This will have an impact on specific renewable-energy technologies and will be discussed when relevant. However, it will not significantly affect energy and renewable-energy patent applications data. A listing of the classifications used for energy patent applications and renewable-energy patent applications is provided in Table 3.

The model for federal energy R&D initially uses panel estimation just as the previous model did. However, results indicate that panel estimation is not appropriate for the energy data. This is confirmed by testing the statistical significance of dummy variables for each year. Due to the fact that panel estimation does not provide a good fit for the data, the data is pooled and estimated with OLS. This will be discussed in greater detail in the results section.

Model 3 – Renewable Energy

$$ln(RPATS)_i = \beta_0 + \beta_1 ln(RRD)_i + \beta_2 ln(RRD)_i^2 + \beta_3 ln(RES)_i + \beta_4 ln(RES)_i^2 + \beta_5 ln(ARTS)_i + \beta_6 (OPEN)_i + \beta_7 ln(INV)_i + \beta_8 ln(FDI)_i + \beta_9 ln(FEES)_i + \beta_{10} ln(GDP)_i + \epsilon_i$$

Model three examines the relationship between renewable-energy patent applications and federal renewable-energy R&D funding. The renewable-energy model is similar to the previous model. It is a log-linear model estimated with OLS and it includes the same explanatory variables with the exceptions of the patent applications and R&D variables. For this model the R&D variable is federal renewable-energy R&D expenditures, and the patents variable is renewable-energy patent applications. A database for renewable-energy patents is developed using the classification system developed by Popp (2002). See Table 3 for a listing of the specific patent classes used.

It is not possible to extract patent application data in the areas of bio-energy, hydropower, or additional "other" types of renewable energy. However, the federal renewable-energy R&D data provided by the IEA includes R&D funding for these areas. Thus, in order for the renewable-energy R&D expenditure data to coincide with the renewable-energy classifications used in the development of the renewable-energy patent applications database, total bio-energy R&D expenditures, total hydropower R&D expenditures, and "other renewables" R&D expenditures are subtracted out of the federal renewable-energy R&D expenditure data. The renewable-energy technologies included in this study consist of solar energy, photovoltaic cells, wind energy, ocean energy, and geothermal energy. A very brief discussion of each of these technology types is provided below.

Solar Energy

"Solar technologies use the sun's energy to provide heat, light, hot water, electricity, and even cooling, for homes, business, and industry" (National Renewable Energy Laboratory). Popp's classifications break down solar-energy patents into four categories – a set that includes such items as collecting heat from solar energy and the use of solar energy to generate power, a set for solar cells, a set for batteries used to store solar energy, and a set that relates to the process of manufacturing solar energy devices (Popp, 2002).

Photovoltaic Cells

Photovoltaics, also called solar cells, convert sunlight directly into electricity. The photovoltaic cells are made of semi-conducting materials. When sunlight is absorbed by these materials, the solar energy knocks electrons loose from their atoms, allowing the electrons to flow through the material to produce electricity. This process of converting solar into electricity is known as the photoelectric effect (National Renewable Energy Laboratory). R&D expenditures in the area of photovoltaic cells focus on new materials that can be used in fuel cells (Popp 2002). More specifically, R&D emphasizes innovative research, thin-film development, manufacturing R&D, and systems development and reliability (National Renewable Energy Laboratory).

Wind Energy

Wind energy is generated when wind rotates a turbine, turning a shaft and producing energy. "Wind power is the closest to being economically competitive in the bulk power market" (Popp, 2002). Wind energy has achieved success in the United States with over eighty percent of the world's wind-generated electricity being produced in California.

R&D efforts for wind energy are focused on improvements in the design of wind turbines (Popp, 2002).

Ocean Energy

"Generating technologies for deriving electrical power from the ocean include tidal power, wave power, ocean thermal energy conversion, ocean currents, ocean winds and salinity gradients. Of these, the three most well-developed technologies are tidal power, wave power and ocean thermal energy conversion" (California Energy Commission). Tidal power comes from large tidal differences. Wave energy conversion takes advantage of the ocean waves caused primarily by interaction of winds with the ocean surface. Ocean thermal energy conversion is limited to tropical locations (California Energy Commission).

Geothermal Energy

Geothermal energy is energy generated from the heat of the earth, which can come from the following four sources: hydrothermal, geopressured, hot dry rock, and magma. According to the National Renewable Energy Laboratory, hydrothermal resources are currently the only geothermal energy technology being used, but in the future it may be possible to use the heat of deep, hot, dry rock formations of the Earth's crust and possibly the heat from the earth's magma. Hydrothermal resources rely on hot water and steam close to the earth's surface to generate electric power. Geopressured resources are water and dissolved methane existing under conditions of high pressure. Hot dry rock resources utilize naturally hot rock formations at depths that are accessible from the earth's surface. Finally, magma resources utilize hot molten rock. R&D efforts for geothermal energy focus on drilling technologies that will allow geothermal-energy resources to be accessed (Popp, 2002).

Results

The first step in the analysis of each model is an examination of summary statistics. For each model, summary statistics are generated using only those observations in the regression estimations. The minimum and maximum values show that the raw data for many of the variables spans a wide range, illustrating the need to use the logarithmic transformation of the data. Summary statistics for each variable are reported in Table 4.

Model 1 - Total

As previously stated, Model 1 examines the relationship between total federal R&D expenditures and total patent applications, and is estimated using panel estimation. For panel estimation it is necessary to determine whether fixed or random effects are appropriate. This determination is done with a Hausman test. The Hausman test tests the null hypothesis that the coefficients estimated by the efficient random effects estimator are the same as the ones estimated by the consistent fixed effects estimator. The null hypothesis should be rejected if the resulting p-value is greater than the desired level of significance and should not be rejected if the resulting p-value is less than the desired level of significance. The Hausman test results in a p-value of 0.0027 indicating that fixed effects are appropriate.

The data is tested for autocorrelation and heteroskedasticity. Due to the nature of the data, the presence of autocorrelation could not be directly tested. In place of a direct test for autocorrelation, a generalized least squares (GLS) regression is estimated and the results from the estimation are compared to the results of an OLS estimation of model 1.

GLS estimation is essentially OLS estimation applied to a transformed model that satisfies the classical assumptions necessary to attain best linear unbiased estimators. The model is transformed by regressing the dependent variable on the independent variables in the difference form, which is obtained by subtracting a proportion of the value of a variable in the previous time period from its value in the current time period.

As a result, estimates from a GLS regression are corrected for autocorrelation. In order to indirectly test for the presence of autocorrelation in the data, the results of the GLS estimates are compared to the OLS estimates of model 1. The results of the two estimations, which are reported in Table 5, are very similar. The estimates from the GLS estimation are corrected for autocorrelation and since the OLS estimates are very similar to these results, it is concluded that there is no autocorrelation of the data. This result is somewhat expected due to the relatively low number of observations for each country.

Testing for heteroskedasticity is done directly with a Breusch-Pagan/Cook-Weisburg test for heteroskedasticity, which tests the null hypothesis of constant variance. Results from the Breusch-Pagan/Cook-Weisburg test indicate that at ten percent significance heteroskedasticity is not present in the data, but at five percent significance it is. These results are obtained by applying the Breusch-Pagan/Cook Weisburg test to the OLS estimates, not the panel estimates. When applied to the panel estimates heteroskedasticity is less likely since the use of panel estimation is one way to correct for heteroskedasticity. Thus, it is possible that when estimated with panel estimation there will be no heteroskedasticity at five percent significance. Regardless, the data is corrected for heteroskedasticity using White's procedure for heteroskedasticity-consistent standard errors. Results from the Breusch-Pagan/Cook-Weisburg test are reported in Table 6.

Fixed effects regression estimates for Model 1 are listed in column (i) of Table 7. The results of the estimation indicate that total federal R&D, the number of researchers as a percentage of the total labor force, and the number of scientific and technical journal articles are statistically significant and positively related to patent applications. Additionally, total R&D-squared is statistically significant and negative, indicating diminishing marginal returns to total federal R&D. The partial coefficient estimate for total federal R&D must be calculated as a marginal effect. The calculation results in an elasticity of -0.18.

An elasticity value of -0.18 indicates that increases in total federal R&D result in slight decreases in patent applications. More precisely, a one percent increase in total federal R&D results, on average, in a 0.18 percent decrease in total patent applications. Previous studies using data for all types of R&D (including federal, private, institutional, etc.) have found elasticies in the range of 0.2 to 0.6 (see Hall et al., 1984; Pakes and Griliches, 1984; Hausman et al., 1984; Ulku, 2004). Studies examining federal R&D have found results similar to those of this study, which is a weak negative elasticity of patents to federal R&D. For instance, Musolesi (2007) uses heterogeneous panel estimations for 16 OECD countries and finds elasticity values of -0.41 using ARDL equations and -0.052 using Pooled Mean Group Estimators.

Openness and FDI are significant, but have a negative relationship with patent applications, which is not expected. While FDI has characteristics similar to those of investment, it also captures aspects of technology sharing between countries. Ulku

(2004) finds that countries that do not have effective R&D sectors benefit from technology sharing. As a result, a measure of technology spillover should be positive in countries without effective R&D sectors, but may be negative or insignificant in countries with effective R&D sectors. It may be possible to examine this relationship further by separating the sample into countries with effective R&D sectors and those without effective R&D sectors and observing the signs of the openness and FDI variables.

Investment, GDP, and patent application filing fees are insignificant. Investment has a very low t-value of 0.30, and was insignificant in every model that was estimated. As a result, investment is dropped and the model is re-estimated. The results of the re-estimation are listed in column (ii) of Table 7.

After dropping investment, GDP and patent application filing fees remain insignificant. GDP is positive as expected and patent application filing fees are negative as expected. The partial coefficient estimate indicates that patent applications are inelastic to changes in fees, which may be due to the fact that the highest fee for filing a patent application in this data set is $770 whereas the potential return on a patent greatly exceeds this amount. An increase in the price of filing a patent application will therefore not greatly affect the number of patent applications. Previous studies have undertaken the task of assigning patent values. The results from these studies vary significantly with values ranging from several thousand dollars to upwards of one-hundred thousand dollars for average returns. See Griliches (1990) and Schankerman and Pakes (1986) for a discussion of this topic. Overall, the model provides a good fit for the data, indicated by an F-value of 23.61.

Model 2 – Energy

Model 2 examines the relationship between federal energy R&D expenditures and energy patent applications. Panel estimation is applied. The estimation results, which are reported in columns (iii) and (iv) of Table 7, indicate that federal energy R&D expenditures are positive and significant with diminishing marginal returns, and patent application filing fees are significant and negative. However, all other explanatory variables in the model are insignificant and the F-value of 2.65 for the model is low, suggesting that panel estimation may not provide a good fit for the data.

In order to test this, a dummy variable for each year is created and the data is pooled and estimated using OLS. Two models are estimated. The first is the full model and the second is a model including only federal energy R&D, federal energy R&D-squared and GDP. Both estimations yield insignificant results for the year dummies, confirming the suspicion that the data no longer possesses the properties of panel data. Estimation results for year dummy regressions are reported in columns (i) and (ii) of Table 8.

Energy OLS estimates are reported in column (i) of Table 9. The estimates that are reported have been corrected for heteroskedasticity using White's procedure for heteroskedasticity-consistent standard errors. Results from the Breusch-Pagan/Cook-Wiseburg test indicate the presence of heteroskedasticity in the data, indicated by a χ^2 value of 27.72. Investment is insignificant and is again dropped from the model. Federal energy R&D funding is insignificant while federal energy R&D funding-squared is significant. Because of the nature of the relationship of the two R&D variables, federal energy R&D-squared is dropped from the model. After dropping federal energy R&D-squared, federal energy R&D is significant with an elasticity of 0.13, meaning that a one percent increase in federal energy R&D results, on average, in a 0.13 percent increase in energy patent applications.

Rather than the negative relationship found for total R&D and total patent applications, the relationship for federal energy R&D and energy patent applications is positive. These results are in agreement with those of Popp (2002). Popp's study includes an estimate with unweighted patent stocks and an estimate with weighted patent stocks. Government R&D is insignificant in the unweighted model. In the weighted model, however, government R&D is significant with a long-run elasticity of -0.052, again suggesting that federal R&D may crowd out private R&D.

Popp (2002) repeats the estimation while separating out the effects of federal energy R&D before and after 1981, which coincides with the election of Reagan. The estimates indicate that federal energy R&D funding occurring after 1981 has a positive relationship with energy patent applications due to a change in the nature of federal energy R&D enacted by Reagan in 1981. All of the federal energy R&D efforts estimated for this study occurred after 1981. As a result, the positive effects from this study, although larger in magnitude (0.13 compared to 0.048), are in agreement with Popp's findings.

Popp's results, however, are based only on patent applications applied for by Americans, whereas the current study includes patent applications originating from 19 different countries. It is possible that other countries underwent similar changes in the nature of federal R&D in 1981 as a result of changes in the nature of U.S. energy R&D. However, for a better investigation of the validity of this conclusion, similar country specific variables should be included in the model for each country in order to control for any such changes.

The other explanatory variables indicate similar results to those of the first model, with a few exceptions. Again, researchers as a percentage of the labor force and the number of scientific and engineering journal articles are both positive and significant. Both variables, however, have a much higher elasticity than in the first model, which may be due to the higher degree of scientific nature for the energy sector compared to all sectors as a whole. Foreign direct investment is negative and significant as before. Patent application filing fees are also negative, but are now statistically significant.

Additionally, the elasticity of energy-related patent applications to patent application filing fees is larger in magnitude with an elasticity of -0.54, compared to an elasticity of -0.099 for patent application filing fees in the model for total R&D. The higher elasticity value and the statistical significance for energy patent application filing fees indicates that an increase in fees leads to a larger decrease in energy patents compared to total patent applications. This could be an indication of the value of energy patents. If energy patents have a lower expected value than all patents as a whole, inventors will be more likely to reduce patenting of energy-related innovations as a result of a fee increase. It could also be a result of a higher percentage of energy patents with a value of zero. Additional research is needed to confirm these conclusions.

Two differences from the previous model include the fact that researchers as a percentage of the total labor force exhibit diminishing marginal returns and the fact that openness is positive rather than negative as before. This change in openness could possibly be explained by dividing the data into different samples per Ulku (2004) or by examining the specific nature of trade as it pertains to energy and energy technologies. Overall, the model provides a good fit for the data with an adjusted-R^2 value of 0.9504, indicating that the model explains 95.04 percent of the total variability in energy patent applications.

Model 3 – Renewable Energy

Model 3 examines the relationship between renewable-energy patents and federal renewable-energy R&D expenditures. The results for renewable-energy show a similar pattern to that of the model for energy. The initial full model panel estimation shows the expected relationship of a positive R&D term with diminishing marginal returns, but again all other explanatory variables in the model, with the exception of patent application filing fees, are insignificant. With an F-value of 2.22, the model does not provide a good fit for the data. Because of this, the significance of year dummy variables are tested and found to be insignificant, confirming that panel estimation does not provide a good fit for the data. Panel estimation results are reported in columns (v) and (vi) of Table 7 and estimation results for dummy variables are reported in columns (iii) and (iv) of Table 8.

Since panel estimation does not provide a good fit for the renewable-energy data, the data is pooled and estimated with OLS. Renewable-energy OLS estimates are reported in column (ii) of Table 9. The estimates that are reported have been corrected for heteroskedasticity using White's procedure for heteroskedasticity-consistent standard errors. Results from the Breusch-Pagan/Cook-Wiseburg test indicate the presence of heteroskedasticity with a χ^2 value of 21.32. Once again investment is insignificant and is dropped from the model. Federal renewable-energy R&D-squared is also dropped because the renewable-energy R&D term is insignificant when renewable-energy R&D-squared is in the model.

Researchers as a percentage of the labor force positively influence renewable-energy patent applications with an elasticity of 2.977. This value is very close to the elasticity of total patent applications to researchers of 2.097 and is smaller than the elasticity of energy patent applications to researchers of 4.761. The number of journal articles is also positive with an elasticity of 1.243. Openness, FDI, and patent application filing fees all have results similar to the energy estimates in both sign and elasticity. One difference between the estimates for renewable-energy and the estimates for the previous two models is that GDP is significant for renewable-energy whereas it was insignificant in the previous two models. The elasticity of renewable-energy patents to GDP is 0.245, indicating that, on average, a one percent increase in GDP leads to a 0.245 increase in renewable-energy patent applications.

A second major difference between the estimates for renewable-energy and the estimates for energy is the federal R&D funding variable. Federal energy R&D funding was found to be positive and significant with an elasticity of 0.13. However, federal renewable-energy R&D funding is insignificant. Furthermore, the elasticity of renewable-energy patent applications to federal renewable-energy R&D funding is 0.0034, indicating that federal renewable-energy R&D has a very small effect on renewable-energy innovation. Figure 1 provides a graphical representation of changes in federal renewable-energy R&D funding over time and changes in the number of renewable-energy patent applications over time. It is fairly clear from the graph that during the period of 1974-1997 there is not a strong relationship between federal renewable-energy R&D funding and renewable-energy patent applications. Overall, the model provides a good fit for the data with an adjusted-R^2 value of 0.9488.

Two major arguments exist for the weak and insignificant relationship between federal renewable-energy R&D and renewable-energy patents. The first argument centers on insufficient levels of federal R&D investment in renewable-energy technologies in order to achieve scientific and technological breakthroughs.

The U.S. federal government invests about $100 billion per year in R&D. Of the $100 billion, about 2% is invested in energy research, down from 10% in the 1980s. The 2005 federal budget reduced energy R&D by 11% and the American Association for the Advancement of Science projects an additional 18% decline by 2009. Private investment in energy R&D has also fallen. Between 1991 and 2003 private energy R&D fell by 50% and now comprises less than one-fourth of all energy R&D (Nemet and Kammen, 2007). Ongoing reductions of federal energy R&D budgets have continued despite the warnings of numerous scientists and experts arguing that much greater levels of energy R&D are needed. For example, "a 1997 report from the President's Committee of Advisors on Science and Technology and a 2004 report from the bipartisan National Commission of Energy Policy each recommended doubling federal R&D spending" (p 746). Other groups have called for much larger increases in federal energy R&D – some on the scale of the Apollo or Manhattan projects (see Schock et al., 1999; Davis and Owens, 2003; Kammen and Nemet, 2005; and Hendricks, 2004).

Similar trends in energy and renewable-energy R&D investments are occurring not just in the U.S., but in other countries as well. Figures 2, 3, and 4 show the federal R&D budgets for total R&D, energy R&D, and renewable energy R&D, respectively, for all 19 countries in the study. The graphs clearly indicate that the aggregated data follows the same trends as the U.S data. Total federal R&D increased steadily from 1981 to 2004.

Energy R&D rose sharply from 1974 to 1980 and then declined steadily through 2004. Renewable-energy R&D also rose sharply from 1974 to 1980 and then fell sharply until 1989 when it leveled off and remained mostly unchanged around 500 million U.S. dollars.

At current technology levels, reductions in green house gas emissions are not possible without stifling economic growth and the development prospects for billions of people worldwide (Sachs, 2008). What is needed in order to achieve a reduction in green house gas emissions without stifling economic growth is advancement in the state of technology of renewable energy. In order to achieve this advancement in technology large increases in R&D investments are needed. A recent article states that, "enormous advances in energy technology will be needed to stabilize atmospheric carbon-dioxide concentrations at acceptable levels… There is no question about whether technological innovation is necessary – it is. The question is, to what degree should policy focus directly on motivating such innovation" (Pielke, Jr, et al., 2008)?

The burden to supply the R&D investments necessary to achieve technology advancement in renewable-energy will fall upon federal governments. The lack of industry investment in technology areas suggests that the federal government must play a role not only in increasing direct investment but also in correcting the market and regulatory obstacles that discourage investment in new technology (Duke and Kammen, 1999). Large increases in federal R&D are necessary in order to achieve the initial difficult and costly breakthroughs that will make additional innovation in the area of renewable-energy technologies more attainable and bring renewable-energy technologies out of their nascent states and into more mature and useable forms.

One concern with very large increases in government R&D investment is crowding-out of other R&D investment. Previous studies, including this study, have found evidence of crowding-out associated with government R&D. However, past evidence with Apollo- or Manhattan-like government initiatives have not resulted in crowding-out of R&D. Nemet and Kammen (2007) tested for the presence of crowding-out associated with major government R&D projects, such as the Apollo or Manhattan projects, and found that evidence of government crowding out is weak or nonexistent. "In fact, large government R&D initiatives were associated with higher levels of both private sector R&D and R&D in other federal programs… One interpretation of these results is that the signal of commitment that a large government initiative sends to private investors outweighs any crowding-out effects associated with competition over funding or retention of scientists and engineers" (Nemet and Kammen, 2007).

The second major argument for the small and statistically insignificant relationship between federal renewable-energy R&D and renewable-energy patent applications centers on the issue of technology implementation and creating a market for renewable-energy. There are several issues contributing to the difficulty of implementing renewable-energy technologies. These include the negative environmental impacts associated with renewable-energy technologies, the high cost of generating electricity with renewable-energy technologies, and the very large investments that have already been made to create the energy infrastructure currently in use.

Contrary to what many individuals may believe, renewable-energy technologies do have potential environmental hazards. One example of solar-energy technology with environmental hazards is solar receiver systems, which have the potential to release toxic chemicals (Baechler and Lee, 1991) and to create microclimate alterations (Mihlmester et al., 1980). Photovoltaic cells have potential environmental hazards due to the use of toxic chemicals such as cadmium sulfide and gallium arsenide in their manufacture, which makes the disposal of inoperative cells a major issue (Holdren et al., 1980). Wind turbines can disrupt bird migration patterns and increase bird deaths as birds fly into the wind turbines (Clarke, 1991; Kellett, 1990). Shadow flicker from wind turbines have also been known to cause irritation, disorientation, and seizures in humans (Steele, 1991). The hazards associated with hydroelectric power include coverage of agricultural land by water, disruption of existing plant and animal species in the ecosystem, alterations of shore lines, displacement of people, and increases in water loss due to evaporation (Flavin, 1985; Barber, 1993). Lastly, the use of biomass can result in air pollution, increased soil erosion, and reductions of nutrient levels in the soil (Pimentel et al., 1984; Pimentel, 1992).

In addition to the potential hazards listed above, a major issue for many types of renewable-energy technologies is the amount of land space required to generate a significant amount of electricity. For example, Pimentel et al. (1994) estimates that biomass could generate 5 quadrillion BTUs of energy by 2050 (for reference, 1991 total U.S. energy use was 85.1 quadrillion BTUs). In order to generate this much electricity, 75 million hectares of land are needed, which is an area larger than the state of Texas. Table 10 lists several different types of renewable-energy technologies and the necessary land requirements associated with them. Each type of renewable-energy requires significantly more land area than traditional power sources such as coal. Available land area will become an increasing concern as demand for living space and crop land increases with growing populations.

The current high costs associated with energy production from renewable-energy technologies is also a barrier to the implementation of renewable-energy technologies. Currently there is low demand for renewable-energy because the cost of producing energy with renewable-energy technologies is higher than traditional methods of energy production, such as coal. The IEA World Energy Outlook 2001 Insights publication rated bioenergy, off-shore wind energy, solar thermal energy, photovoltaic cells, and geothermal energy as having either high or very high current costs. Only onshore wind energy and hydroelectric energy (large scale only) were reported as having low current costs. Testing the relationship between the costs of renewable-energy technologies and changes in renewable-energy technology innovations will be a focus of future research for this study.

An additional barrier to the implementation of renewable-energy technologies is the very large investments that have been made in traditional energy sources, especially in developed countries, and the reluctance to discontinue the use of those energy sources. For instance, governments and private companies invest large sums of money to construct coal-burning power plants, off-shore oil excavation rigs, pipelines to carry oil across the country, etc. Assuming a cheap, clean, and effective source of renewable-energy became available, there will still be reluctance to switch to new sources of energy because of the large investments that have been made in existing energy sources. Consumers will be hesitant to buy a new vehicle that runs on a different energy source because of the investment that has been made in their current vehicle. Numerous examples can be cited to illustrate the reluctance to convert to a renewable-energy source. Because of this, there is likely to be a long turnover period associated with the conversion to a new energy supply. This argument will be tested in future research by observing the relationship between renewable-energy patent applications and investments in traditional energy sources such as coal.

Additional evidence of this argument exists in the fact that, compared to OECD countries, much greater levels of growth in total primary energy supply of renewable energy is expected to occur in developing countries. Developing countries have not made large investments in an existing energy infrastructure and therefore do not face the same reluctance and turnover time that developed countries with a large existing energy infrastructure face. Total primary energy supply of renewable energy for OECD countries is expected to increase by 51.7% from 1997 to 2020. Developing countries, over the same time period, are expected to see a 128.7% increase in total primary energy supply of renewable energy. Total primary energy supply of renewable energy by region is reported in Table 11.

Conclusions

The estimation results for total patents, energy patents, and renewable-energy patents all indicate a strong positive association between patent applications and researchers as a percentage of the labor force and patent applications and the number of scientific and technical journal articles. This indicates that increases in human capital and the existing knowledge stock result in greater levels of innovation. Additionally, patent application filing fees are negative in all three models and significant in two of the three models. This leads to the conclusion that increases in patent fees result in a decrease in the number of patent applications, although the magnitude of the decrease is greater for energy and renewable-energy patents than for total patents. Further research is needed in order to make conclusions regarding the impact that openness and FDI have on innovation.

The results for the effectiveness of federal R&D are mixed at this point. For total federal R&D and total patent applications, estimates indicate a weak negative relationship. Estimates for federal energy R&D and energy patents indicate a weak positive relationship. Estimates for federal renewable-energy R&D and renewable-energy patent applications are insignificant. Several arguments exist that provide potential explanations for this insignificant relationship. Further research will be undertaken to verify the validity of these arguments and to expand upon the overall understanding of the relationship between federal renewable-energy R&D funding and renewable-energy innovation.

Future Research

There are several areas of future research for this study. Two specific areas include examining the relationship between the cost of producing electricity with renewable-energy source and the number of renewable-energy patent applications and the relationship between investments in traditional energy sources and the number of renewable-energy patent applications. The approach that will be used to study the impacts of the costs of energy production with renewable-energy sources will consist of including the costs of electricity production for each type of renewable-energy technology as a regressand in the renewable-energy model. Two approaches can be used for this. The first approach will consist of using the average cost of all renewable-energy technologies as an explanatory variable with renewable-energy patent applications as the dependent variable. The second approach will consist of using patent application data and electricity production cost data for each type of renewable-energy technology – including solar energy, photovoltaic cells, wind energy, ocean energy, and geothermal energy. The data for the different technology types will then be pooled and estimated. A negative relationship between the cost of producing electricity with renewable-energy technologies and renewable-energy patent applications will support the argument that higher costs of electricity generation associated with renewable-energy technologies are preventing the further development and implementation of renewable-energy technologies.

A similar approach will be used to test the relationship between investments in existing energy infrastructures and the number of renewable-energy patent applications. For this, data for various types of traditional energy technologies (i.e. coal power, oil, etc) will be included as regressands in the existing model for renewable-energy. A negative relationship between renewable-energy patents and investments in the existing energy infrastructure will support the hypothesis that large investments into existing energy technologies prevents further development and implementation of renewable-energy technologies.

The work that has been done thus far provides a framework for further investigation into the effectiveness of specific types of renewable-energy technologies. Additional research into the areas of specific renewable-energy technologies will make it possible to answer additional questions. For instance, does solar-energy research yield a higher number of patents in comparison to other renewable-energy technologies? If so, what is different about the nature of solar-energy and the nature of solar-energy R&D efforts that make it more effective at generating innovation than the other technology types? Could other technology types "learn" from the success of solar-energy and/or should additional resources be used for solar-energy due to its success? Understanding the behavior of these technology types will allow for a greater understanding of the various types of renewable-energy and will allow for a comparison of the relative effectiveness of federal R&D efforts for the various types of renewable-energy technologies. Furthermore, it will make it possible to attain a better understanding of the renewable-energy results already obtained.

Additional efforts will also be made to increase the number of observations in the estimates. The data available for nearly all of the variables make it possible to increase the time span of the study to include the years 1979 to 1997 rather than starting the study in 1985. The number of researchers employed for each country and the number of scientific and engineering journal articles both limit the data such that the study must begin in 1985. Therefore, future research will focus on developing alternative variables that effectively measure the effects of human capital and the existing stock of knowledge on innovation that are available for a greater number of years. It would also be of great interest to expand the study to more recent years in order to see how the effectiveness of federal renewable-energy R&D changes as renewable-energy increases in importance and in public awareness. Currently, the database developed by Hall, Jaffe, and Trajtenberg (2001) contains data only through 1999. Therefore, expanding the data to include more recent years may not be possible, but the possibility will be explored.

Understanding the relationship between renewable-energy R&D funding and changes in innovation is an important step in the development of renewable-energy technologies. A feasible source of renewable-energy will be necessary in the future. Without this, the world will face increasingly higher energy prices as nonrenewable-energy sources are depleted. More importantly, however, a renewable source of energy is necessary for the sustainability of life.

References

Baechler, M.C., and A. D. Lee, 1991, "Implications of environmental externalities assessments for solar thermal power plants", *Solar Engineering*, pp. 151-158.

Barber, M, 1993, "Why More Energy? The hidden cost of Canada's Cheap Power", *Forests, Trees and People Newsletter,* No. 19, pp. 26-29.

Bound, John, et al, 1984, "Who Does R&D and Who Patents?" NBER Conference Report. Chicago and London: University of Chicago Press, pp. 21-54.

California Energy Commission, http://www.energy.ca.gov/.

Clarke, A, 1991, "Wind Energy Progress and Potential", *Energy Policy*, Vol 19, pp. 742-755.

Coe, David T., and Helpman, Elhanan, 1995, "International R&D Spillovers" *European Economic Review*, Vol 39, pp. 859-887.

Davis, G.A., and Owens, B., 2003, "Optimizing the Level of Renewable Electric R&D Expenditures Using Real Options Analysis", *Energy Policy*, vol 31, pp. 1589-1608.

Duke, Richard, and Kammen, Daniel M., "The Economics of Energy Market Transformation Programs", *The Energy Journal*, Vol. 20, No. 4, pp. 15-64.

Energy Information Administration, International Energy Outlook 2006, http://www.eia.doe.gov/oiaf/ieo/world.html

Evenson, R.E., 2001, "Patents, R&D, and Invention Potential: International Evidence," *AEA Papers and Proceedings*, Vol. 83(2), pp. 463-468.

Flavin, C, 1985, "Renewable Energy at the Crossroads", Center for Renewable Resources Washington, DC.

Griliches, Zvi, 1989, "Patents: Recent Trends and Puzzles," *Brookings Papers:*

Microeconomics, 291-319.

Griliches, Zvi, 1990, "Patent Statistics as Economic Indicators: A survey," *Journal of Economic Literature*, Vol. xxviii, pp. 1661-1707.

Hall, B.H., Griliches, Zvi, and Hausman, J.A., 1986, "Patents and R&D: Is There a Lag?" *International Economic Review*, Vol. 27(2), pp. 265-283.

Hall, Bronwyn, H., Jaffe, Adam B., and Trajtenberg, Manuel, 2001, "The NBER Patent Citaions Data File: Lessons, Insights and Methodological Tools," NBER Working Paper Series, Working Paper No. 8498, JEL No. O3.

Hausman, Jerry A., Hall, Bronwyn, and Griliches, Zvi, 1984, "Econometric Models for Count Data with an Application to the Patents – R&D Relationship," *Econometrica*, Vol. 52(4), pp. 909-938.

Hendricks, B., 2004, Testimony to the House Committee on Resources Oversight Hearing on Energy Supply and the American Consumer, Executive Director, Apollo Alliance. U.S. House of Representatives, Washington, DC.

Heston, Allen, Summers, Robert, and Aten, Bettina, Penn World Table Version 6.2, Center for International Comparisons of Production, Income and Prices at the University of Pennsylvania, September 2006.

Holdren, J.P., Morris, G., and Mintzer, I., 1980, "Environmental Aspects of Renewable Energy", *Annual Review of Energy*, Vol. 5, pp. 241-291.

International Energy Agency http://www.iea.org/Textbase/stats/rd.asp

International Energy Agency, 2001, World Energy Outlook Insights.

Jaffe, Adam, 1986, "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patents, Profits, and Market Value," *American Economic Review*, Vol. 76(5), pp. 984-1001.

Kammen, D.M., and Nemet, G.F., 2005, “Reversing the Incredible Shrinking U.S Energy R&D Budget” *Issues in Science and Technology,* vol 22 (1), pp. 84-88.

Kellet, J., 1990, “The Environmental Impacts of Wind Energy Developments”, *Town Planning Review*, 61, pp. 139-154.

MacKinnon, J., White, H., and Davidson, R., 1983, “Tests for Model Specification in the Presence of Alternative Hypothesis; Some Further Results”, *Journal of Economcetics*, Vol 21, pp. 53-70.

Margolis, Robert M, and Kammen, Daniel M, 2001, “Energy R&D and Innovation: Challenges and Opportunities for Technology and Climate Change”, *A Reader in Climate Change Policy*, pp. 1-26.

Meliciani, Valentina, 2000, “The Relationship Between R&D, Investment, and Patents: A Panel Data Analysis,” *Applied Economics*, Vol. 32, pp. 1429-1437.

Mihlmester, P.E., Thomasian, J.B., and Riches, R., 1980, “Environmental and Health Safety Issues”, *Solar Energy Technology Handbook*, pp. 731-762.

Musolesi, Antonio, 2007, “R&D and Productivity in 16 OECD Countries: Some Heterogeneous Panel Estimations,” *Applied Economics Letters,* Vol. 14, pp. 493-496.

National Renewable Energy Laboratory. www.nrel.org

Nemet, Gregory F. and Kammen, Daniel M. 2007, “U.S Energy Research and Development: Declining Investment, Increasing Need, and the Feasibility of Expansion,” *Energy Policy*, Vol. 35, pp. 746-755.

OECD Main Economic Indicators www.oecd.org/statsportal

Pakes, Ariel and Griliches, Zvi, 1980, “Patents and R&D at the Firm Level: A First Look,” *NBER Conference Report. Chicago and London: University of Chicago Press*, pp. 55-72.

Pakes, Ariel and Griliches, Zvi, 1984, "Estimating Distributed Lags in Short Panels with an Application to the Specification of Depreciation Patterns and Capital Stock Constructs," *Review of Economic Studies*, pp. 243-262.

Pielke, Roger Jr, Wigley, Tom, and Green, Christopher, 2008, "Dangerous Assumptions", *Nature*, Vol. 452, No. 3, pp. 531-532.

Pimentel, D., Levitan, L., Heinze, J., Loehr, M., Naegeli, W., Bakker, J., Eder, J., Modelski, B., and Morrow, M., 1984, "Solar Energy, Land and Biota", *Sun World*, 8, pp. 70-73, 93-95.

Pimentel, D., 1992, "Competition for Land: Development, Food, and Fuel", *Technologies For a Greenhouse-Constrained Society*, pp. 325 – 348.

Pimentel, David, Rodrigues, G., Wang, T., Abrams, R., Goldberg, K., Staecher, H., Ma, E., Brueckner, L., Trovato, L., Chow, C., Govindarajulu, U., and Boerke, S., 1994, "Renewable Energy: Economic and Environmental Issues," *BioScience*, Vol. 44, No. 8, pp. 536-547.

Popp, David, 2002, "Induced Innovation and Energy Prices," *The American Economic Review*, Vol. 92(1), pp. 160-180.

Sachs, Jeffrey D., 2008, "Keys to Climate Protection", *Scientific American.*

Sanyal, Paroma, 2003, "Understanding Patents: The Role of R&D Funding Sources and The Patent Office," *Econ. Innov. New Techn*, Vol. 12(6), pp. 507-529.

Schankerman, Mark and Pakes, Ariel, 1986, "Estimates of the Value of Patent Rights In European Countries During the Post-1950 Period," *The Economic Journal*, Vol. 96, pp. 1052-1076.

Scherer, F. M. 1965b, “Firm Size, Market Structure, Opportunity, and the Output of Patented Inventions,” *American Economic Review*, Vol. 55, pp. 1097-1125.

Schmookler, Jacob. Invention and Economic Growth. Cambridge: Harvard University Press, 1966.

Schock, R.N., et al., 1999, “How Much is Energy Research and Development Worth as Insurance?”, *Annual Review of Energy and Environment*, 24, pp. 487-512.

Steele, A., 1991, “An Environmental Impact Assessment of the Proposal to Build a Wind Farm at Langdo Common in the North Pennines, UK”, *The Environmentalist*, 11, pp. 195-212.

Ulku, Hulya, 2004, “R&D, Innovation, and Economic Growth: An Empirical Analysis,” IMF Working Paper, WP/04/185.

United States Patent and Trademark Office. www.uspto.gov.

World Development Indicators, 2005.

Appendix 1: Tables and Figures

Table 1: Listing of countries included in study

Australia
Austria
Belgium
Canada
Denmark
France
Germany
Hungary
Ireland
Italy
Japan
Netherlands
New Zealand
Norway
Spain
Sweden
Switzerland
United Kingdom
United States

Table 2: Description of Variables

TPATS:	Total Patent Applications from the United States Patent and Trademark Office.
TRD:	Total federal research and development expenditures. Research and development data is available from the OECD Main Science and Technology Indicators and is reported in millions of constant 2000 US dollars.
RES:	Total number of full time researchers employed in a country divided by total labor force of the country and multiplied by 100. The number of researchers for each country is available from the OECD Main Science and technology indicators database and labor force data is available from World Development Indicators Database. According to the WDI, total labor force comprises people who meet the International Labor Ogranization definition of the economically active population: all people who supply labor for the production of goods and services during a specified period. It includes both the employed and the unemployed. In general the labor force included the armed forces, the unemployed, and first-time job-seekers, but excludes homemakers and other unpaid caregivers and workers in the informal sector.
ARTS:	Total scientific and engineering journal articles. Data is available from WDI. The WDI's description of this variable is the number of scientific and engineering articles published in the following fields: physics, biology, chemistry, mathematics, clinical medicine, biomedical research, engineering and technology, and earth and space sciences.
OPEN:	Open refers to a measure of a country's openness as developed by the Penn World Tables. It is measured as the sum of a country's exports and imports, divided by real GDP per capita.
INV:	This is a measure of gross fixed capital formation measured in constant 2000 U.S. dollars. This data is available from WDI and is defined by WDI as land improvements (fences, ditches, drains, and so on); plant, machinery, and equipment purchases; and the construction of roads, railways, and the like, including schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings.
FDI:	Foreign Direct Investment data is measured in current U.S. dollars and is available from WDI. The WDI description of this variable is net inflows of investment to acquire a lasting management interest (10 percent or more of voting stock) in an enterprise operating in an economy other than that of the investor. It is the sum of equity capital, reinvestment of earnings, other long-term capital, and short-term capital as shown in the

balance of payments. This series shows total net, that is, net FDI in the reporting economy from foreign sources less net FDI by the reporting economy to the rest of the world.

FEES: United States Patent and Trademark Office fee for filing original patent application. Fees are measured in U.S dollars.

GDP: GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Data are in constant U.S. dollars.

EPATS: Energy Patent Applications from the United States Patent and Trademark Office.

ERD: Federal Energy Research and Development. Data is available from the International Energy Agency and is measured in millions of 2005 U.S. dollars. Federal energy R&D pertains to the areas of energy efficiency, fossil fuels, renewable energy, nuclear fusion and fission, hydrogen and fuel cells, and other power and storage technologies.

RPATS: Renewable-Energy Patent Applications from the United States Patent and Trademark Office.

RRD: Federal Renewable-Energy Research and Development. Data is available from the International Energy Agency and is measured in millions of 2005 U.S. dollars. Federal renewable-energy R&D pertains to the areas of solar energy, wind energy, ocean energy, bio-energy, hydropower, and “other renewables”.

Table 3: Listing and Descriptions of USPTO Patent Classifications for Energy and Renewable-Energy Patent Applications Databases

Energy

Class	Title
29	Metal Working
48	Gas: Heating and Illumination
60	Power Plants
62	Refrigeration
75	Specialized Metallurgical Processes, Compositions for Use Therein, Consolidated Metal Powder Compositions, and Loose Metal Parts
110	Furnaces
122	Liquid Heaters and Vaporizers
126	Stoves and Furnaces
136	Batteries: Thermoelectric and Photoelectric
148	Metal Treatment
162	Paper Making and Fiber Liberation
164	Metal Founding
165	Heat Exchange
204	Chemistry: Electrical and Wave Energy
208	Mineral Oils: Processes and Products
250	Radiant Energy
290	Prime-Mover Dynamo Plants
416	Fluid Reaction Surfaces (i.e., Impellers)
429	Chemistry: Electrical Current Producing Apparatus, Product, and Process
431	Combustion
438	Semiconductor Device Manufacturing: Process

Renewable-Energy

Class	Title
29	Metal Working
60	Power Plants
62	Refrigeration
126	Stoves and Furnaces
136	Batteries: Thermoelectric and Photoelectric
250	Radiant Energy
290	Prime-Mover Dynamo Plants
416	Fluid Reaction Surfaces (i.e., Impellers)
438	Semiconductor Device Manufacturing: Process

Table 4: Summary Statistics

Varible	Obs	Mean	Std. Dev.	Min	Max
tpats	206	5793.893	14107.82	28	77699
log(tpats)	206	6.752	1.937	3.367	11.260
trd	206	3683.111	6779.931	59.375	29357.48
log(trd)	206	7.020	1.595	4.084	10.287
log(trd)^2	206	51.819	23.037	16.678	105.829
epats	178	404.882	922.76	0	3972
log(epats)	178	4.178	1.915	0	8.287
erd	178	617.711	986.307	1.468	3806.736
log(erd)	178	5.159	1.811	0.384	8.245
log(erd)^2	178	29.882	17.979	0.147	67.972
rpats	185	227.768	537.82	0	2345
log(rpats)	185	3.510	1.927	0	7.760
rrd	185	30.912	49.137	0.092	263.926
log(rrd)	185	2.291	1.681	-2.391	5.576
log(rrd)^2	185	8.059	7.834	0.005	31.088
researchers	185	150422.2	266641.4	2813	1159908
res/labor	185	0.497	0.184	0.143	1.005
(res/labor)^2	185	0.0028	0.002	0.0002	0.010
articles	185	27024.5	46350.28	653	202887
log(articles)	185	9.352	1.264	6.482	12.220
openness	185	56.899	30.780	13.446	150.354
investment	185	2.25e+11	3.67e+11	7.30e+09	1.55e+12
log(investm)	185	25.172	1.351	22.711	28.069
fdi	185	9.72e+09	1.49e+10	3.93e+07	1.06e+11
log(fdi)	185	22.128	1.491	17.488	25.387
gdp	185	1.16e+12	1.93e+12	3.84e+10	8.65e+12
log(gdp)	185	26.8	1.376	24.371	29.788
fees	185	548.919	191.439	300	770
log(fees)	185	6.24	0.379	5.704	6.646

Table 5: Model 1 Estimation Results for GLS and OLS

	GLS	OLS
Variables	column i	column ii
Constant	-6.884 (-3.79)***	-6.884 (-3.96)***
R&D	-0.785 (-4.99)***	-0.785 (-4.86)***
R&D^2	0.057 (5.56)***	0.057 (5.41)***
Researchers	3.374 (4.03)***	3.374 (3.93)***
Researchers^2	-171.61 (-2.15)**	-171.61 (-2.10)**
Articles	1.097 (11.77)***	1.097 (11.45)***
Openness	0.0094 (7.36)***	0.0094 (7.16)***
Investment	0.159 (0.84)	0.159 (0.82)
FDI	-0.243 (-9.44)***	-0.243 (-9.18)***
GDP	0.272 (1.28)	0.272 (1.24)
Fees	-0.253 (-3.30)***	-0.253 (-3.21)***
n	206	206
Wald χ^2	6642.62	……
R^2	……	0.9684

* indicates significance at 10%, ** indicates significance at 5%, ***indicates significance at 1%

note: values in parentheses for GLS estimates are Z-values; values in parentheses for OLS estimates are t-values

Table 6: Breusch-Pagan/Cook-Weisburg Test For Heteroskedasticity Results

	Total	Energy	Renewable-Energy
χ^2	3.47	27.72	21.32
Prob > χ^2	0.0624	0.000	0.000

H_0: Constant Variance

Table 7: Panel Estimation Results

	Total		Energy		Renewable-energy	
Variables	column i	column ii	column iii	column iv	column v	column vi
constant	-20.099	-21.731	-19.394	-16.264	-14.350	-12.332
	(-1.90)*	(-1.79)*	(-1.11)	(-1.16)	(-0.76)	(-0.83)
R&D	1.502	1.488	0.643	0.638	0.106	0.107
	(2.77)**	(2.75)**	(3.26)***	(3.26)***	(1.81)*	(1.85)*
$(R\&D)^2$	-0.120	-0.118	-0.059	-0.058	-0.018	-0.018
	(-2.58)**	(-2.57)**	(-2.89)**	(-2.88)***	(-1.13)	(-1.13)
researchers	2.134	2.097	1.630	1.559	0.748	0.706
	(2.53)**	(2.56)**	(0.95)	(0.92)	(0.43)	(0.41)
$(researchers)^2$	-35.759	-36.779	1.899	10.929	74.816	81.047
	(-0.66)	(-0.66)	(0.02)	(0.09)	(0.55)	(0.62)
articles	0.404	0.402	0.105	0.112	-0.145	-0.139
	(2.91)***	(2.82)**	(0.40)	(0.43)	(-0.50)	(-0.49)
openness	-0.006	-0.006	-0.006	-0.006	0.005	0.005
	(-1.76)*	(-1.80)*	(-0.93)	(-0.91)	(0.75)	(0.77)
fdi	-0.029	-0.028	-0.021	-0.021	-0.038	-0.037
	(-1.91)*	(-1.97)*	(-0.62)	(-0.61)	(-1.03)	(-1.03)
investment	0.086	……	-0.115	……	-0.074	……
	(0.30)	……	(-0.30)	……	(-0.18)	……
gdp	0.645	0.790	0.964	0.731	0.842	0.693
	(1.34)	(1.67)	(1.00)	(1.28)	(0.81)	(1.13)
fees	-0.088	-0.099	-0.318	-0.296	-0.260	-0.248
	(-1.34)	(-1.72)	(-1.11)**	(-2.37)**	(-1.84)*	(-2.02)**
n	206	206	178	178	185	185
F	70.08	23.61	2.65	2.95	2.22	2.48

* indicates significance at 10%, ** indicates significance at 5%, ***indicates significance at 1%

Table 8: OLS estimates with year dummy variables

	Energy		Renwable-Energy	
Variables	column i	column ii	column iii	column iv
constant	-4.980	-16.939	-7.312	-29.842
	(-1.61)	(-4.86)***	(2.87)***	(-15.28)***
R&D	0.0789	0.056	-0.056	-0.040
	(0.89)	(0.43)	(1.10)	(-0.51)
$(R\&D)^2$	0.006	0.039	0.018	0.018
	(0.58)	(2.59)***	(1.58)	(1.10)
researchers	4.795		3.523	
	(3.50)***		(2.69)***	
(researchers)	-191.389		-104.876	
	(-1.49)		(-0.85)	
articles	1.054		1.195	
	(7.96)***		(9.18)***	
openness	0.004		0.005	
	(2.45)**		(3.05)	
fdi	-0.187		-0.220	
	(-4.81)***		(-5.62)***	
investment	-0.266		-0.204	
	(-1.03)		(-0.80)	
gdp	0.449	0.733	0.450	1.25
	(1.52)	(5.08)***	(1.53)	(16.22)***
fees	-0.767		-0.673	
	(-3.34)***		(-3.26)***	
yr85	(dropped)	-0.202	(dropped)	-0.165
		(-0.67)		(-0.54)
yr86	-0.099	(dropped)	-0.056	(dropped)
	(-0.60)		(-0.33)	
yr87	-0.054	-0.131	-0.036	-0.188
	(-0.34)	(-0.44)	(-0.22)	(-0.62)
yr88	0.062	-0.030	0.146	-0.053
	(0.37)	(-0.10)	(0.86)	(-0.17)
yr89	-0.019	-0.068	-0.069	-0.258
	(-0.11)	(-0.23)	(-0.42)	(-0.86)
yr90	0.086	0.010	-0.008	-0.226
	(0.52)	(0.03)	(-0.05)	(-0.74)
yr91	0.214	-0.147	0.199	-0.268
	(1.30)	(-0.47)	(1.25)	(-0.87)
yr92	0.323	-0.029	0.140	-0.304
	(1.83)*	(-0.09)	(0.84)	(-0.97)
yr93	0.230	0.027	0.075	-0.280
	(1.39)	(0.09)	(0.47)	(-0.94)
yr94	0.105	0.021	0.061	-0.195
	(0.65)	(0.07)	(0.38)	(-0.64)
yr95	0.197	0.143	0.022	-0.291
	(1.25)	(0.47)	(0.14)	(-0.99)
yr96	0.201	0.223	0.112	-0.122
	(1.27)	(0.74)	(0.72)	(-0.42)
yr97	(dropped)	-0.044	(dropped)	-0.320
		(-0.14)		(-1.08)
n	178	178	185	185
R-squared	0.9466	0.8421	0.9449	0.8421

* indicates significance at 10%, ** indicates significance at 5%, ***indicates significance at 1%

Table 9: Pooled OLS Estimates for Energy and Renewable-Energy

Variables	Energy column i	Renewable-Energy column ii
Constant	-5.663 (-2.12)**	-7.77 (-3.82)***
R&D	0.130 (2.39)**	0.0034 (0.10)
Researchers	4.761 (3.77)***	2.980 (2.41)**
$Researchers^2$	-199.69 (-1.82)*	-60.66 (-0.58)
Articles	1.115 (10.70)***	1.243 (10.57)***
Openness	0.004 (2.61)***	0.006 (3.79)***
FDI	-0.196 (-5.78)***	-0.223 (-5.45)***
GDP	0.162 (1.23)	0.245 (2.64)***
Fees	-0.541 (-5.14)***	-0.584 (-5.54)***
n	178	185
R^2	0.9504	0.9488

* indicates significance at 10%, ** indicates significance at 5%, ***indicates significance at 1%

Table 10: Land Requirements for Renewable-Energy Technologies

*Source: Pimentel, David, et al., 1994, "Renewable Energy: Economic and Environmental Issues", *BioScience,* Vol 44 (8), pp 536-547.

Technology Type	Land Required (ha)
Hydroelectric	75,000
Biomass	220,000
Central Receivers	1,100
Solar Ponds	5,200
Wind Power	11,666
Photovoltaics	2,700
Coal	363
Nuclear	48

* Land resource requirements to produce 1 billion kWh/yr of electricity

Table 11: Total Primary Energy Supply of Renewable Energy by Region (Mtoe)

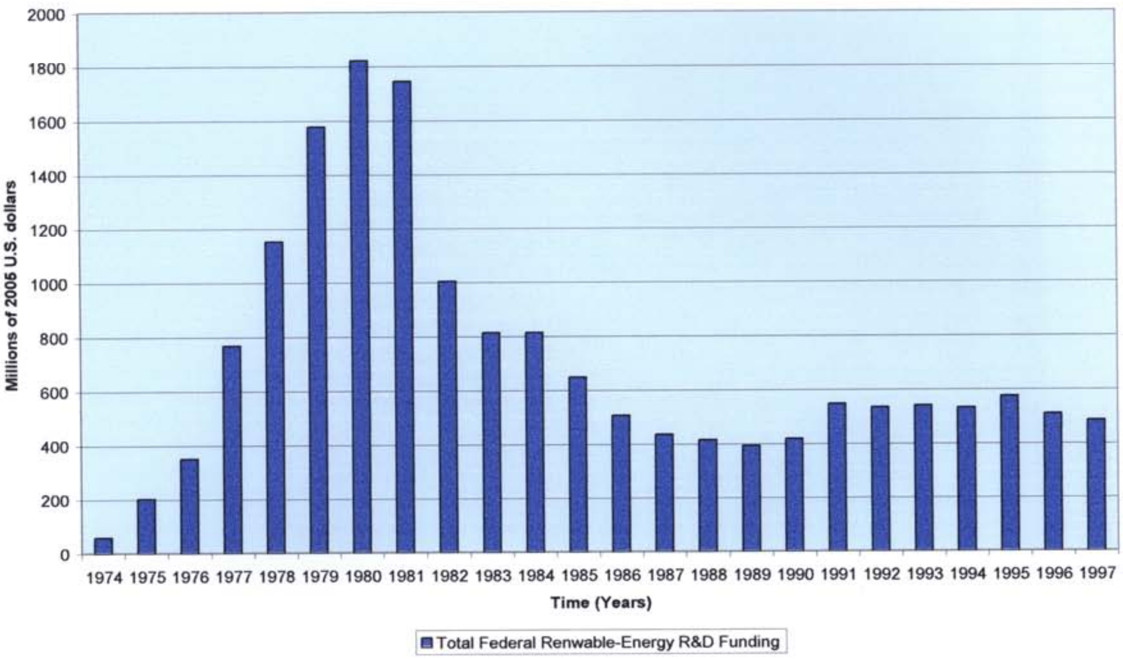
Source: IEA (2000), World Energy Outlook 2000, OECD/IEA

Note: Figures do not include bioenergy in developing countries

	1997	2020
World	410	697
OECD	286	434
Europe	106	190
North America	150	191
Pacific	30	53
Transition Economies	23	32
Developing Countries	101	231
China	17	56
East Asia	15	49
South Asia	9	20
Latin America	53	91
Middle East	2	4
Africa	6	11

Figure 1: Total Federal Renewable-Energy R&D Funding and Total Renewable-Energy Patent Applications, 1974-1997

Total Federal Renwable-Energy R&D Funding



Total Renewable-Energy Patent Applications

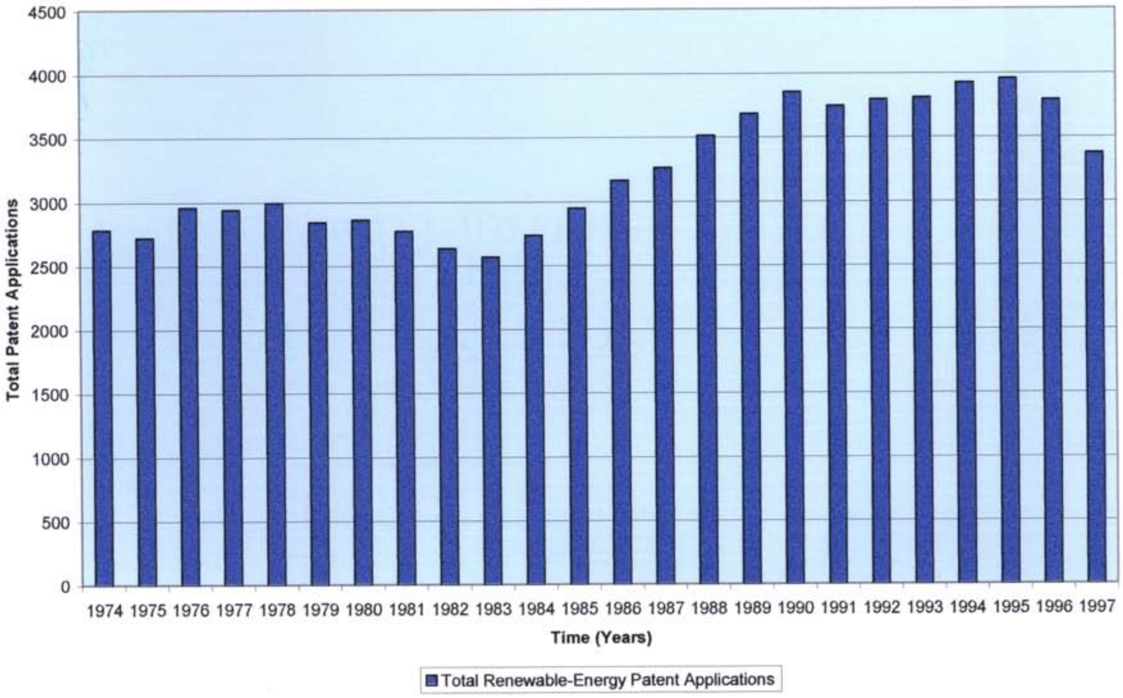


Figure 2: Total Federal Research and Development Funding, 1981-2003

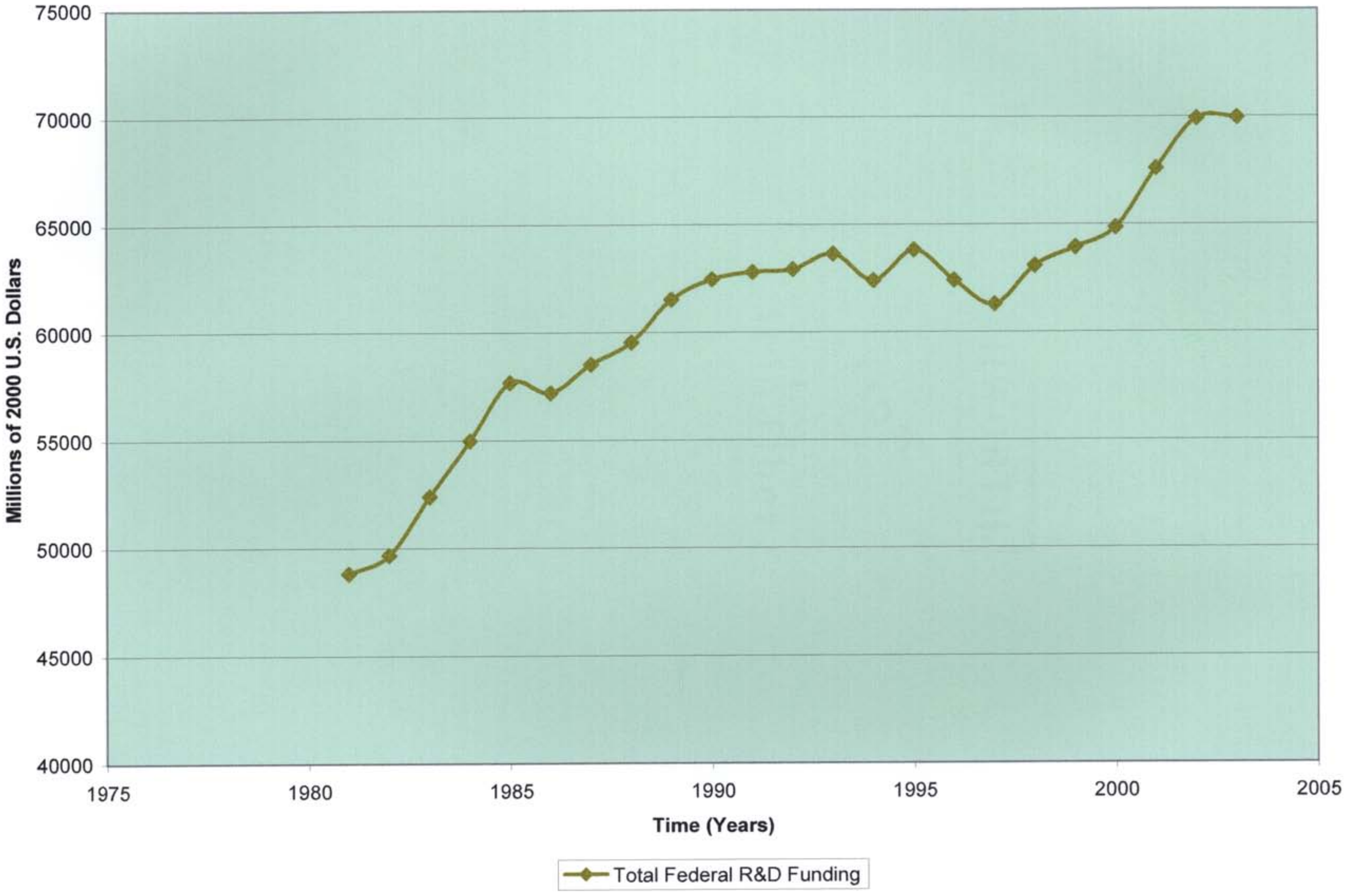


Figure 3: Total Federal Energy Research and Development Funding, 1974-2003

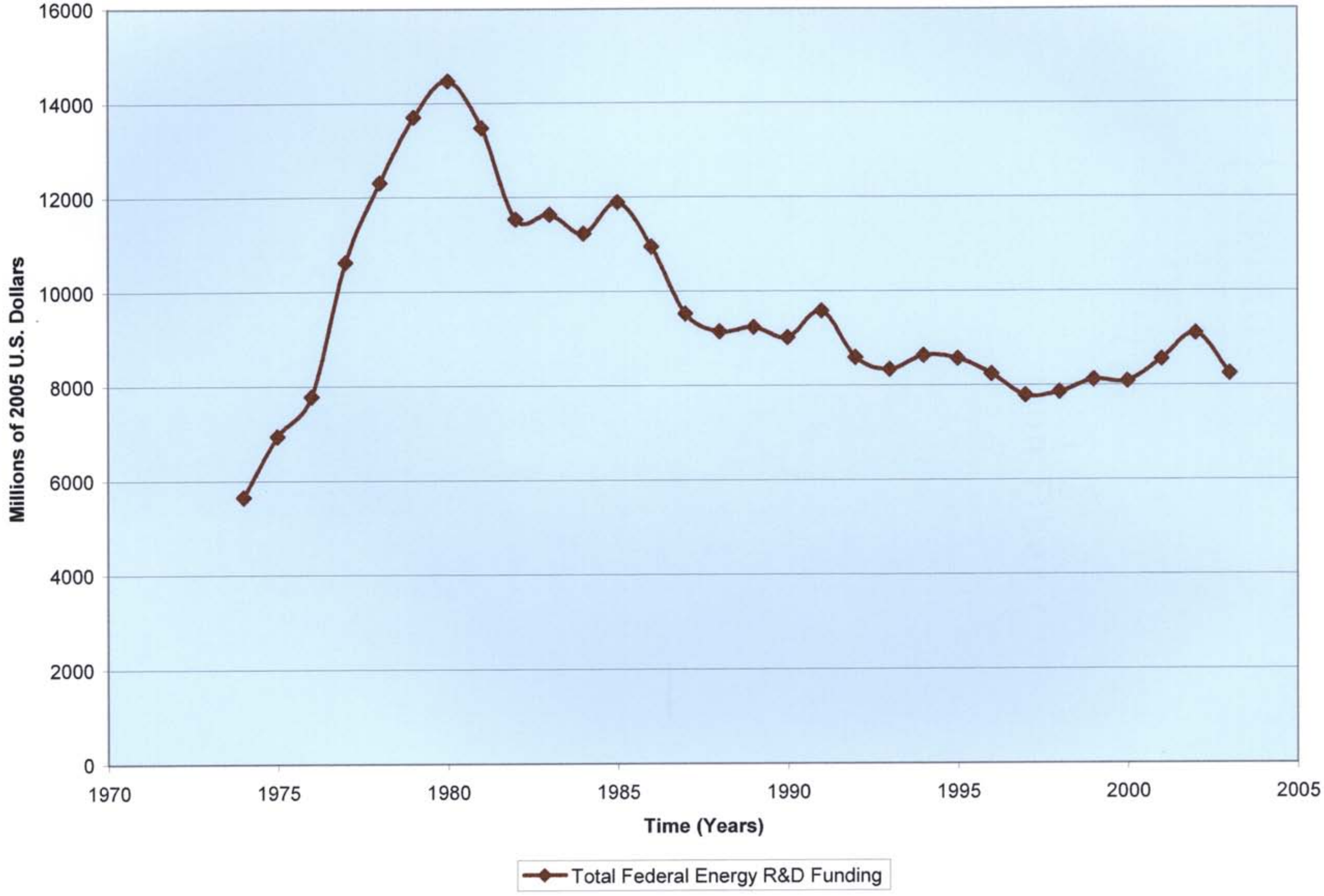


Figure 4: Total Federal Renewable-Energy Research and Development Funding, 1974-2003

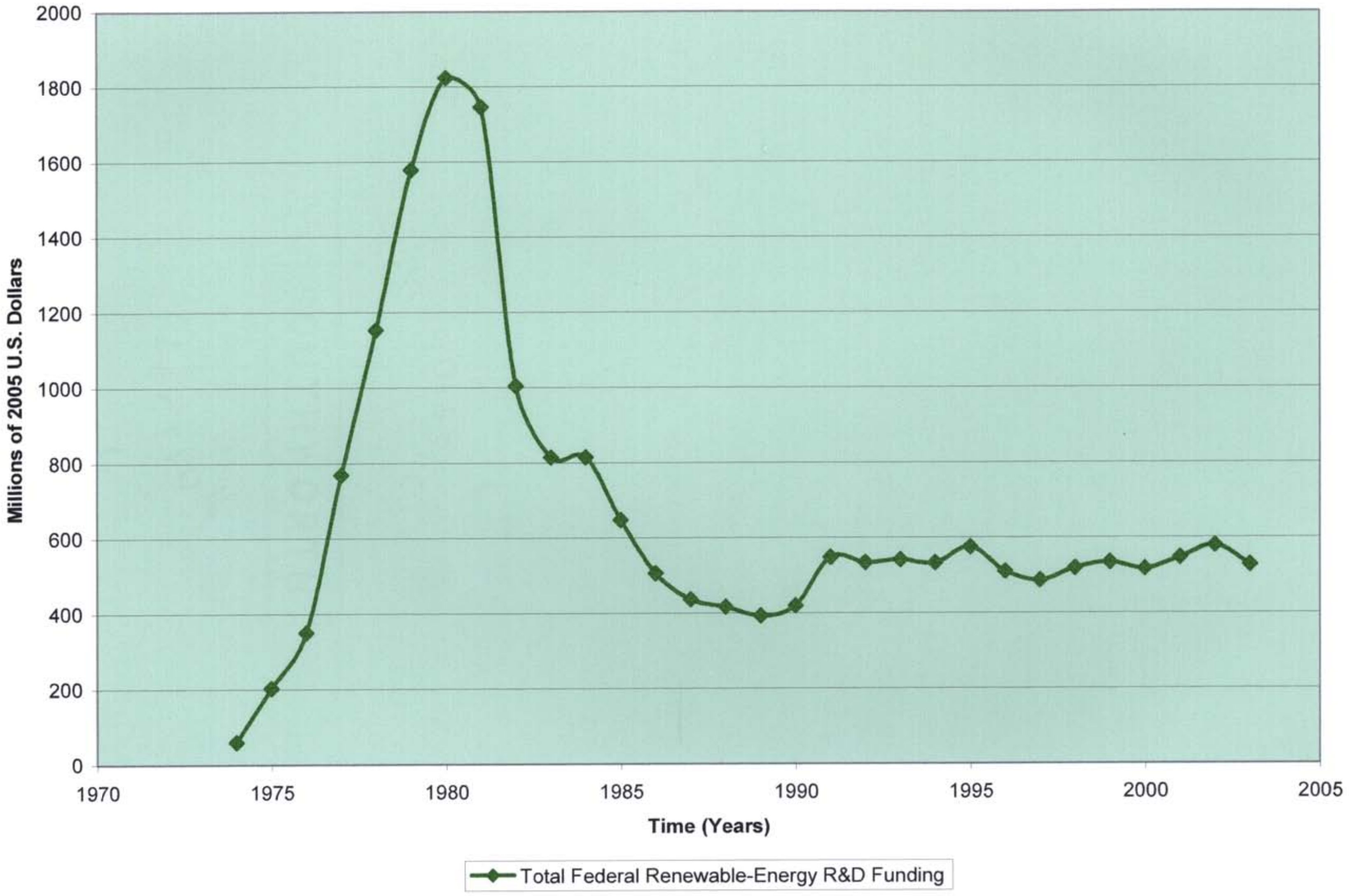
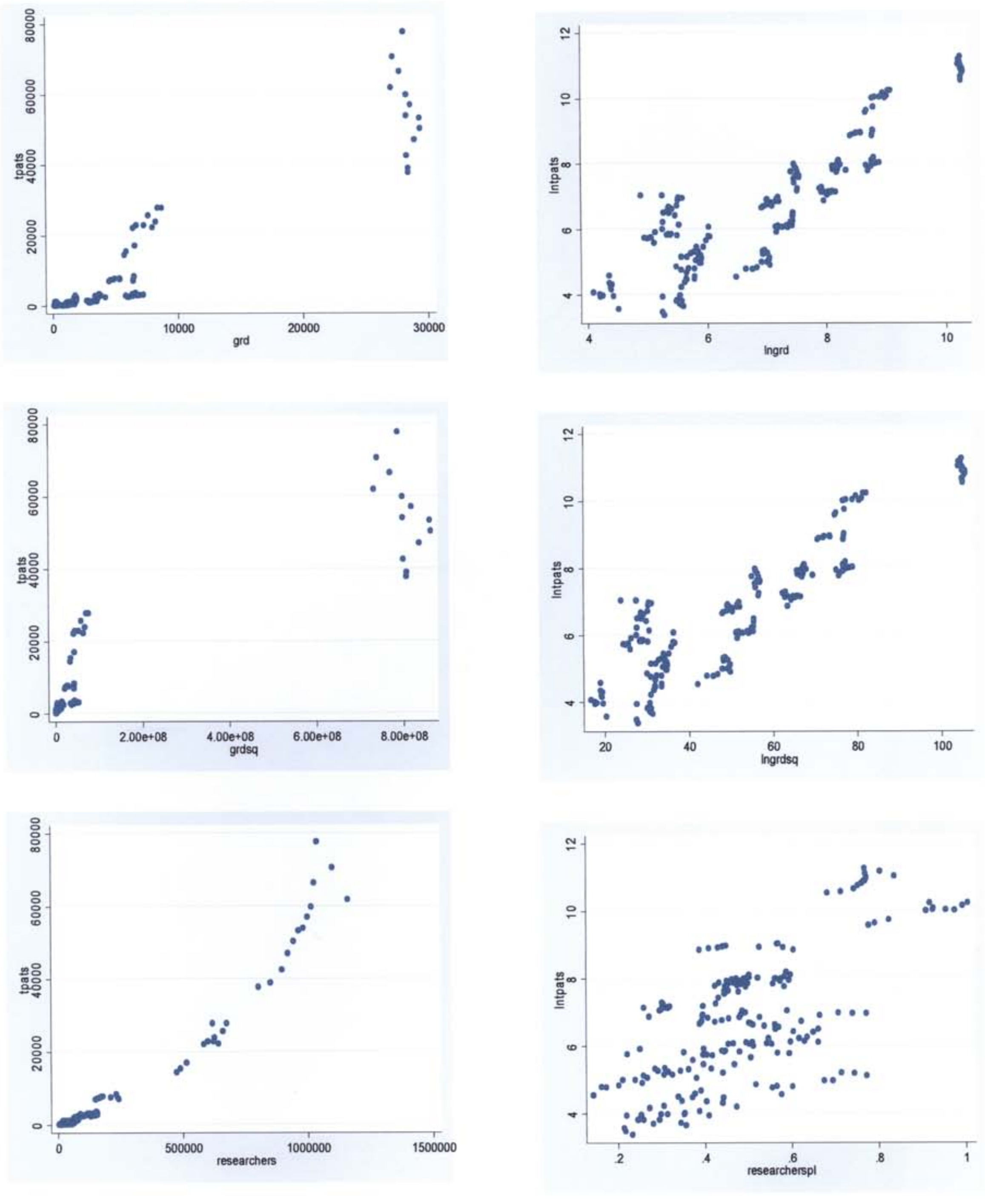
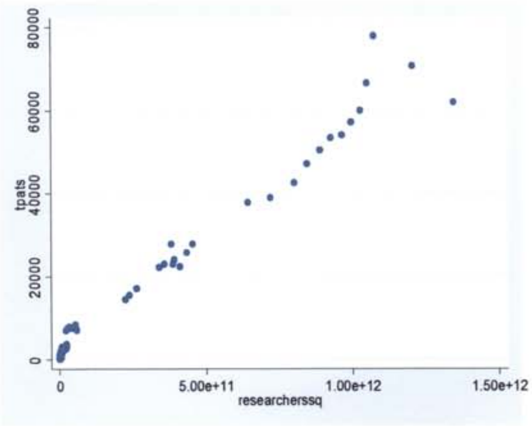
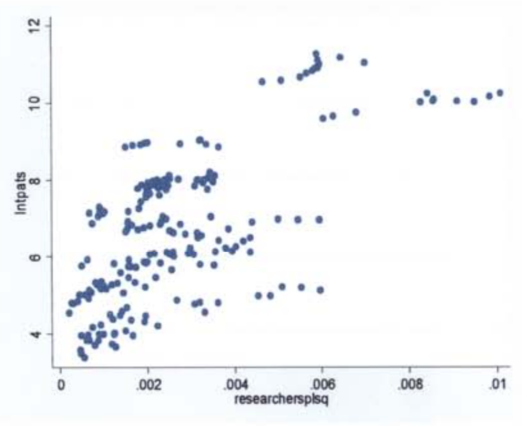


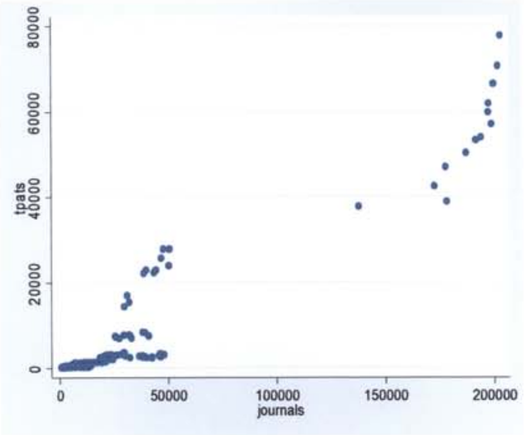
Figure 5: Scatter Plots of Variables

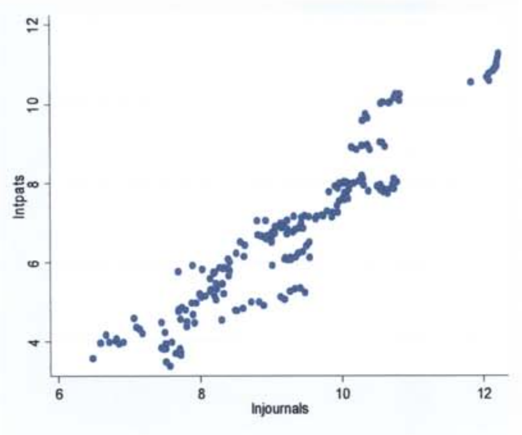
Note: Left Side is Raw Data, Right Side is Log Transformed

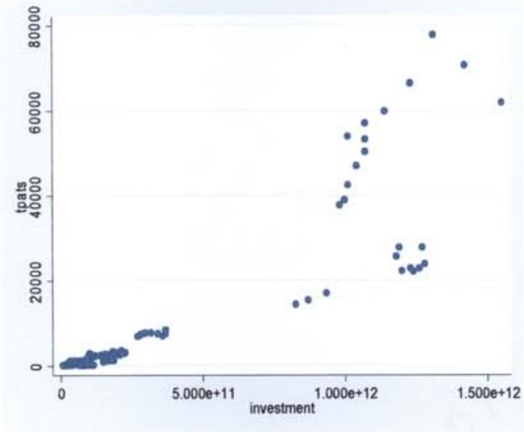


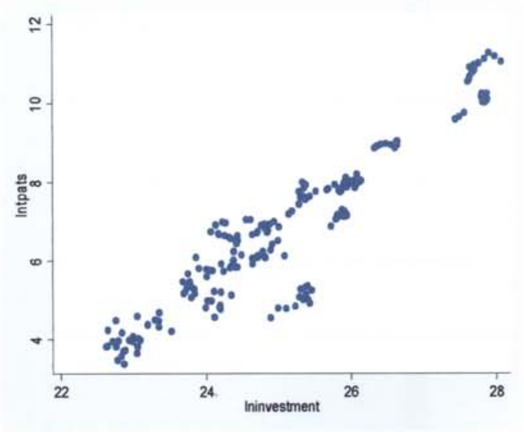

tpats
0
20000
40000
60000
80000
0
5.00e+11
1.00e+12
1.50e+12
researcherssq

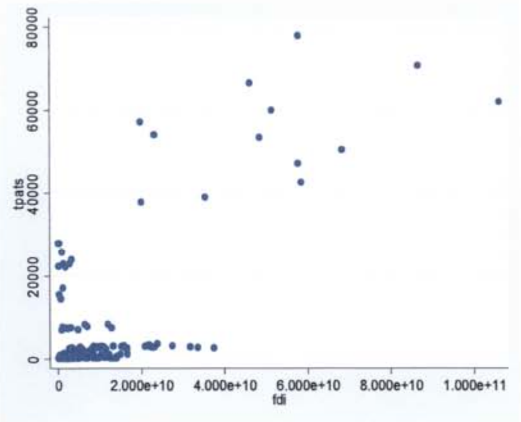

lntpats
4
6
8
10
12
0
.002
.004
.006
.008
.01
researchersplsq

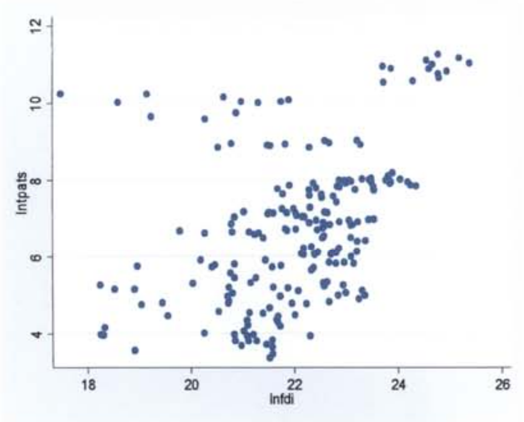

tpats
0
20000
40000
60000
80000
0
50000
100000
150000
200000
journals

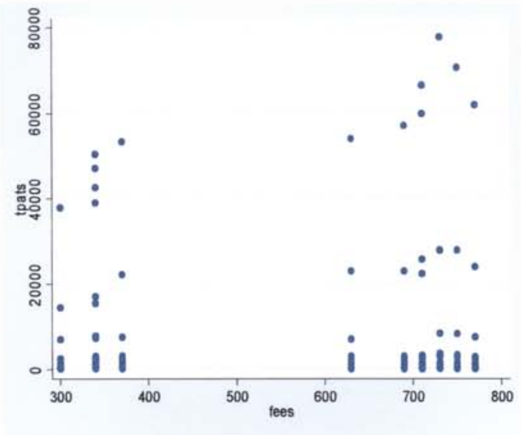

lntpats
4
6
8
10
12
6
8
10
12
lnjournals

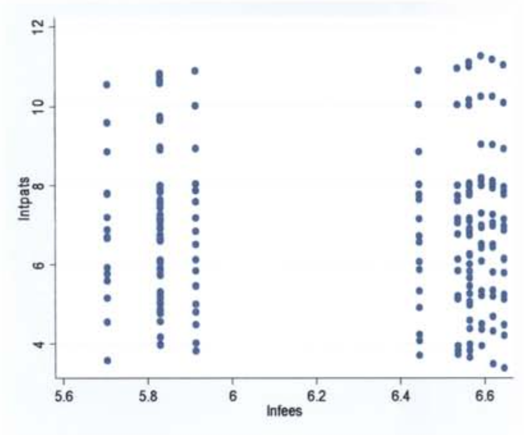

tpats
0
20000
40000
60000
80000
0
5.000e+11
1.000e+12
1.500e+12
investment

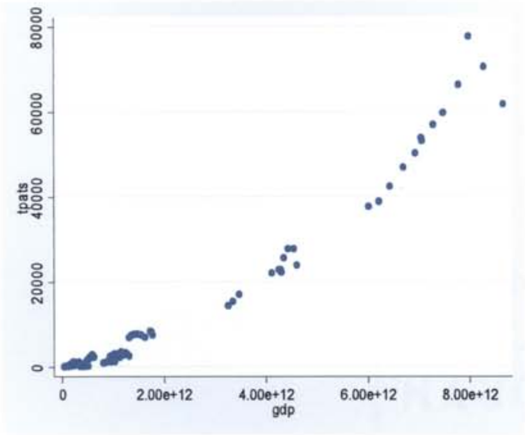

lntpats
4
6
8
10
12
22
24
26
28
lninvestment

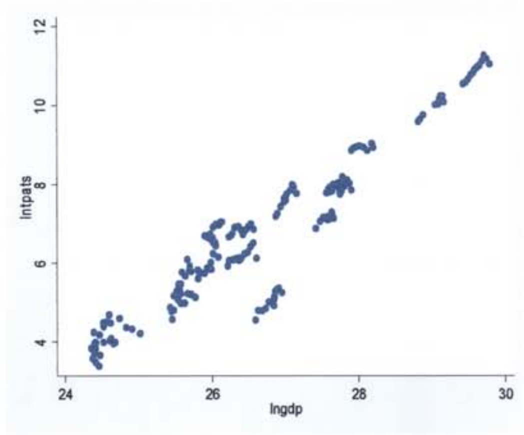

tpats
0
20000
40000
60000
80000
0
2.000e+10
4.000e+10
6.000e+10
8.000e+10
1.000e+11
fdi

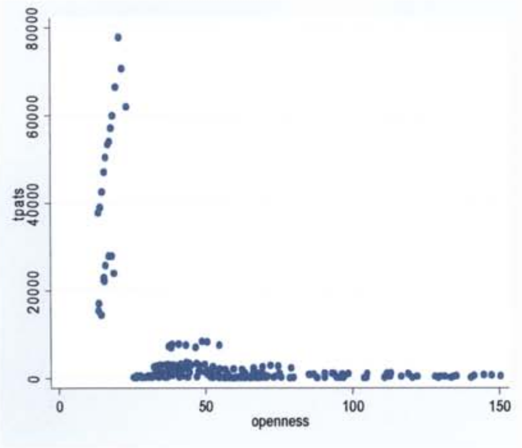

lntpats
4
6
8
10
12
18
20
22
24
26
lnfdi

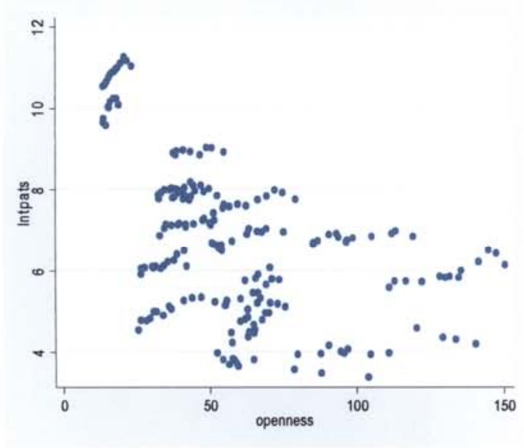

tpats
0
20000
40000
60000
80000
300
400
500
600
700
800
fees


lntpats
4
6
8
10
12
5.6
5.8
6
6.2
6.4
6.6
lnfees


tpats
0
20000
40000
60000
80000
0
2.00e+12
4.00e+12
6.00e+12
8.00e+12
gdp


lntpats
4
6
8
10
12
24
26
28
30
lngdp


tpats
0
20000
40000
60000
80000
0
50
100
150
openness


lntpats
4
6
8
10
12
0
50
100
150
openness