DRAFT

The Dynamic Effects of State-Level Energy and Environmental Policies on Clean Tech Innovation and Employment[1]

An empirical exploration and preliminary findings

Abstract: *This paper explores the influence of state-level energy and environmental policies on clean technology industry innovation and employment using a dynamic panel data analysis. Results do not support the hypothesis that state-level energy and environmental policies have significant positive effects on short-term clean tech innovation or employment. Some individual policies had statistically significant influence, however, the impacts are generally of very small magnitude. It is found that traditional fixed or random effects estimates can overstate the short-term impacts of these policies, compared to dynamic panel estimates which control for state's self-selecting policies and other issues which produce serial correlation. The most significant effects of state-level policies are observed on energy research and service employment concentration. Only certain policies, however, appear to support energy research and service employment, while other policies (which could be characterized as more command and control style regulation) appear to provide disincentives to energy research and service employment. The analysis is limited by the relatively short time period of implementation of many energy and environmental policies and the use of states as the unit of observation.*

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[1]This paper is only for participants in the New England Study Group (NESG) seminar on May 10, 2011. An article on the clean tech economy in New England will complement this exploratory research paper and some of the data for that paper will be presented at the NESG seminar and is available as a background data report available for participants in the May 10th seminar. The authors would like to thank Bo Zhao and Yolanda Kodrzycki for their detailed review and suggestions on earlier drafts of this paper and the Federal Reserve Bank of Boston's New England Public Policy Center for providing support while Professor Gittell was a visiting scholar. We would also like to thank Edinaldo Tebaldi, assistant professor of Economics, Bryant University for his review of drafts and assistance with empirical modeling and data.

Motivation/Introduction

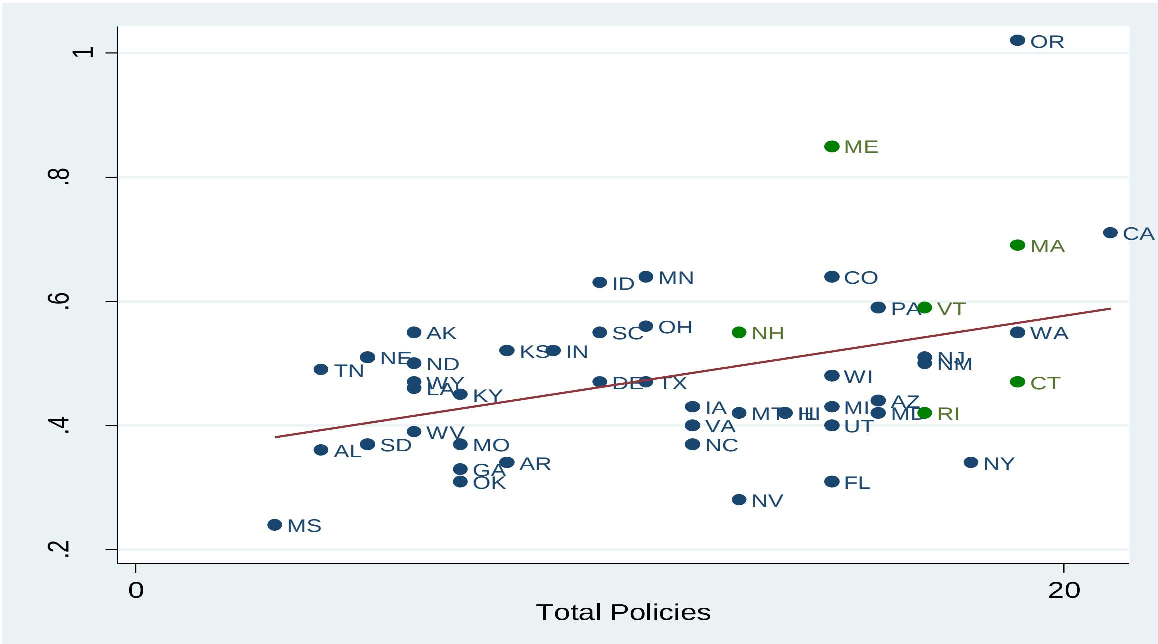
This paper explores how state-level energy and environmental policies influence *clean tech industry development*. These policies have been mostly justified on other criteria -- including reducing dependence on imported energy and based on their environmental, health and national security benefits. Increasingly however, advocacy of such policies has focused on their potential job creating benefits[2]. This study will examine this claim more rigorously. There is also literature discussing the connection between energy and environmental policies and innovation. Jaffe, Newell and Stavin (2005), for example, call for experimenting with policies and systematically evaluating their influence.

A question this research paper will explore is whether states that have been leaders on energy and environmental policy adoption are creating unique opportunities for clean tech industry innovation and employment generation that is not true in other states, but appears to be true in other nations. In Europe, national governments have guaranteed prices for energy from sun or wind and Germany, Spain and other European nations are now among the leaders in global exports in renewable energy, wind power and solar power. Recently, China has emerged as one of the most attractive markets for investment in renewable energy (Ernst & Young, 2010) and it has been suggested that China's leap to leadership has reflected the failure of American lawmakers to pass a national renewable energy standard and agree on a national energy strategy while the Chinese have expanded energy and environmental policies that are reshaping energy related markets in the world's fastest growing economy.

Many of the U.S. states have been active in energy and environmental policies to address climate change in the absence of federal legislation. A motivation for this inquiry is evidence of correlation between state implementation of policies to address climate change and clean technology employment concentration. The scatter-plot below identifies the 50 states' position with regards to clean tech employment concentration (the percentage of total employment in clean tech industries) on the vertical axis and the number of state-level energy and environmental policies states have adopted to address climate change implemented on the horizontal axis using the Pew Charitable Trust's definition of clean tech (Pew Charitable Trust, 2009: Pew Center on Global Climate Change, 2011). The plot depicts a positive correlation between the number of policies implemented and state clean tech employment concentration

[2] See for example the April 13th, 2011 LA times article by Patrick McGreevy "Gov. Brown Signs Law that 33% of Energy be Renewable by 2020" latimes.com/news/local/la-me-renewable-energy-20110413,0,3118203.story

Clean Tech Job Concentration and 21 State-Level Energy and Environmental Policies



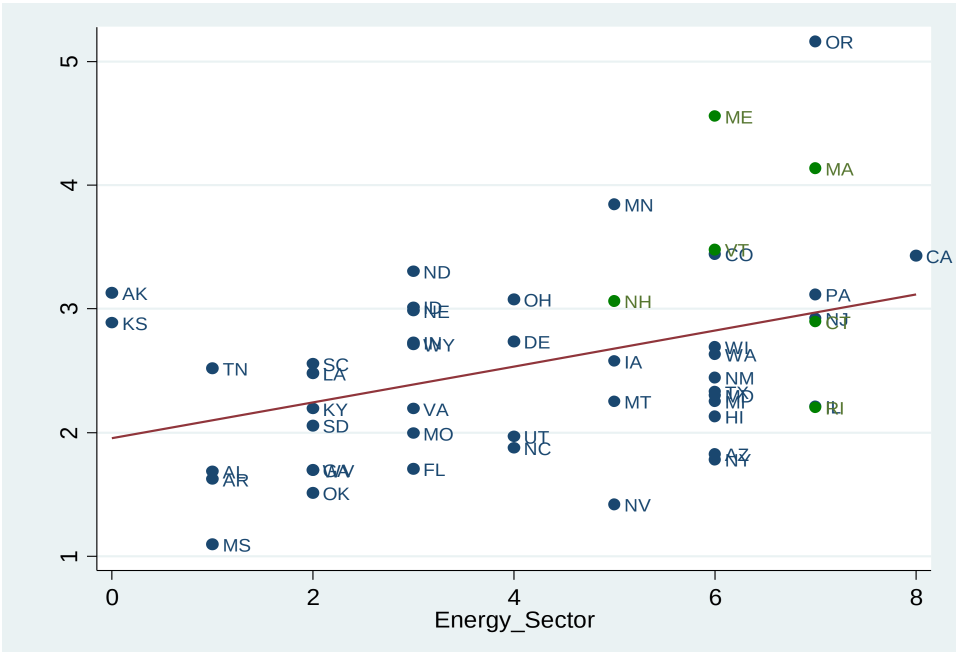
Source: Pew Charitable Trust, 2009; Pew Center on Global Climate Change

California, Maine, Massachusetts, Oregon, and Washington are leaders on both clean tech employment concentration and the implementation of energy and environmental policies, while Mississippi and Alabama are low on both.

Among the state climate change policy areas, the strongest simple correlation is between clean tech job concentration and energy policies, see below. Energy policies comprise 8 of the 21 state-level energy and environmental policies we focus on here.[3]

[3] For more details on climate change polices see table below.

Clean Tech Job Concentration and Energy Policies



Source: Pew Charitable Trust, 2009; Pew Center on Global Climate Change

While these correlations provide some support for the conjecture of benefits from energy and environmental policies in promoting clean tech industry employment, relying on them in policy-making is not appropriate. In particular, with simple correlations there are concerns about unobserved state heterogeneity and related omitted variable bias which may account for industry development separate from the influence of policy. Related to this state may self-select policies. This issue of endogeneity is liable to bias the effects of policies. If energy and environmental policies, for example, tend to be adopted when states are strong in alternative energy use and clean tech industry employment this would produce an upward bias, or conversely a downward bias if adopted when states lag behind in these respects. Furthermore, this static cross-sectional view does not allow examination of policy effects over time, which may not be fixed and instantaneous. To address these concerns, we employ a dynamic panel analysis which examines correlation between changes in the variables, rather than in their levels.

Additionally, a correlation between the number of policies and employment obscures differential effects across the various policies and implicitly assumes their impacts are uniform (which is not found to be the case). In turn, the policies are quantified individually according to the timing of policy enactment, and tested as explanatory variables along with a quadratic policy term to allow for non linear effects over time on clean tech patent development, clean tech employment concentration, and energy research and service employment as the dependent variables of interest. This research is unique in its consideration empirically of the dynamic effects of individual state level policies over time on an industry's development.

Clean Tech Definition

The term *clean tech* in general describes a group of technologies and industries based on the principles of minimizing climate and environmental impacts and using natural resources more efficiently. It includes physical, process and social technologies in renewable energy (e.g., solar, wind, geothermal) generation and energy, materials and resource conservation. As an industry it is mostly contained within a larger high technology industry category and within what has been popularly categorized as the "green economy." It represents in the United States less than 1/8th of high technology and 1/4th of green economy categorizations by most definitions. Clean technology is higher value-added and significantly more export oriented than the broad green economy category which includes many local services including construction.

There is no single or simple definition for clean tech. Here we focus on the clean energy economy definition used by the Pew Trust (2009), see Appendix A for details. The Pew definition is commonly referenced and used.[4] The Pew Trust used micro-level establishment data to count businesses and employment that leverages renewable energy sources, conserves energy and natural resources, reduces pollution and recycles waste. Pew utilized multiple sources to construct their database, including advanced Internet search technology. The Pew Trust definition has 5 sub-categories: clean energy, energy efficiency, environmentally friendly production, conservation and pollution mitigation and training and support. Using the Pew definition .56% of US employment in 2007 was in clean tech; with employment concentration among the states varying from a high of 1% in Oregon to a low of .24% in Mississippi.

We also examine a measure of energy research and service employment to consider the robustness of findings and the impact of energy and environmental policies on an alternative scope of clean tech related employment.

Organization of the Paper

We first ground our exploratory inquiry in economic theory, concepts and terminology and in particular describe how our empirical exploration aligns with different theories of competitive advantage, most notably Michael Porter's diamond model framework. Next, we describe our empirical methodology and data sources used. This is followed by presentation of the empirical results. The paper concludes with a summary of empirical findings, discussion of implications, and identification of potential areas for future inquiry.

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[4] See *The Economist* (August 13, 2009), "Greening the Rustbelt"; *New York Times* (June 10, 2009) "Green Sector Jobs 'Poised for Explosive Growth,' Study Says, Michael Burnham; *Center for American Progress* website "New Map: The Economics of Clean Energy in 50 States"; *Los Angeles Times* (March 25, 2010) "China Takes Lead in Clean Tech Investment" Jim Tankersley and Don Lee; *Huffington Post* (March 18, 2010) "The Five Best Cities for Green Jobs" Dan Shapley; *The Clean Tech Market Authority*, Oct 2009, Clean Tech Job Trends, Ron Pernick.

Literature and Theory

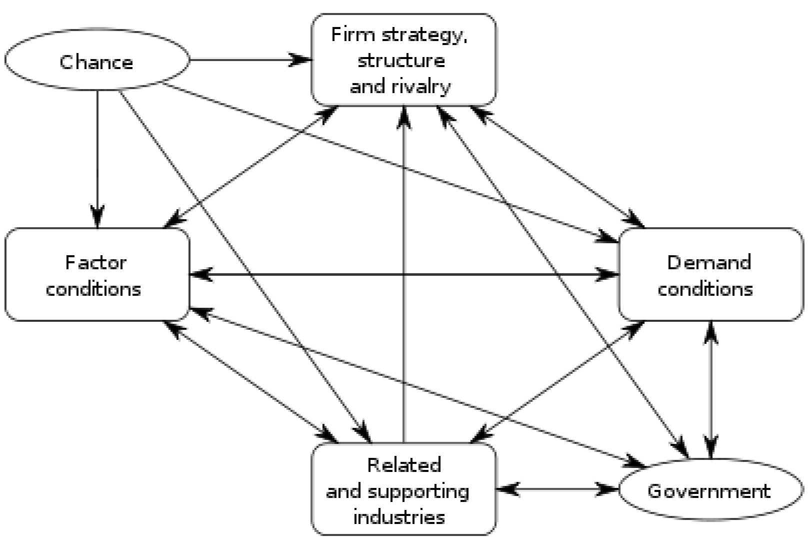
Competitive Advantage Framework

The literature on comparative advantage going back to Ricardo has been a cornerstone in understanding trade and regional production. Heckscher and Ohlin extended the competitive advantage framework of trade being determined by comparative advantages in productivity by relating productivity to factor endowments (Leamer, 1995).

Similarly, the insights of Heckscher and Ohlin have been extended in the new trade theory, primarily associated with the work of Helpman and Krugman (1985). The new trade theory allowed for firm heterogeneity and increasing returns to scale, whereby a region grows on its own strengths in a specific industry. This idea is associated with a networking effect, whereby as more individuals participate in a network (e.g. telephones, social networks, stock exchanges), or work in a given industry in some region (e.g. movies in Hollywood, watches in Switzerland, information technology in Silicon Valley), positive externalities are generated for all in the network as it becomes more profitable since there are a greater number of others with whom to interact, share information and innovate. This over time attracts more individuals and firms to the network and to the region providing positive feedback effects.

Following on the work of Ricardo, Heckscher and Ohlin, Helpman and Krugman and others, Porter (1990) used his diamond model, see below, to determine which firms and industries had competitive advantages in which regions and where and how industry clusters are formed. Porter's model of competitive advantage includes factor conditions, firm strategy, structure and rivalry, demand conditions, related and supporting industries and government along with chance. These together comprise the diamond model.

Porter's Diamond Model of Competitive Advantage



From Porter's diamond model of competitive advantage we focus on the role of local demand, and specifically government (state-level) policy inducing expected shifts in demand as a potentially important element in state- level clean tech industry competitiveness.

Firms that face a sophisticated local market, according to Porter, are likely to sell superior products because the market demands innovation and high quality. Examples of this include the French wine industry and the Italian apparel industry (Doeringer and Crean, 2006). A close proximity to sophisticated consumers enables the firm to better understand the needs and desires of the customers and gain global competitiveness.

In the competitive advantage framework, state-level energy and environmental policies could be thought of as potential triggers to the emergence of a clean tech cluster. According to this line of thinking, energy and environmental policy implementation leadership can create sophisticated local demand (e.g., for renewable energy and energy efficiency), motivate industry innovation and over time foster industry competitive advantage. Exploring this proposition is one of the objectives of this paper. Given current trends globally, a competitive advantage in clean tech industries could beneficially position a state to not only serve its own local demand effectively and efficiently, but also to be well positioned to export its clean technology industry outputs to serve other states and growing global markets.

In addition to local demand in the framework for understanding state level clean technology industry development, it is also important to take into consideration other state level factor conditions --including the availability of skilled labor, the scientific base, and funding to support an industry cluster (Brenner and Muhlig, 2009; Garnsey,1998; Rosegrant and Lampe,1992; Saxenian, 1994).

The factor conditions are often thought of as prerequisites for the emergence of a cluster (Brenner, 2004). They do not determine that a cluster will occur, but influence the likelihood of emergence of a cluster. To support a competitive advantage a factor must be specialized (Porter, 1990) to an industry's particular needs and a trigger may be required (Storper and Walker, 1989; Brenner, 2004)

States can have competitive advantages in industries in which they are particularly good at factor creation for that specialized industry. A question is whether state energy and environmental policies are contributing to this. The implementation of energy and environmental policies and increases in demand for energy efficiency and renewables could encourage clean tech research and development to address the increased demand at lower cost. The research and development activity could result in patents and new venture creation and growth that could attract venture capital funding. The "end result" of the different components can be business and employment growth and increasing industry employment concentration.

We focus on the "final" output of clean technology industry development in the form of clean tech employment concentration. We are also interested in clean tech innovations as measured by patents and how they are influenced by state-level energy and environmental policies

Following from the above competitive advantage concepts, we will consider how clean tech innovation and employment concentration n state economies are influenced by specialized and general high capacity in:

- skilled workers, research and development,
- sophisticated local demand,
- new venture funding, and
- environmental and energy policies

The empirical models we use draw on the theoretical foundations presented above. The proxy for each variable was chosen based on data availability, with the exact data and source discussed below. Any insignificant quadratic terms have been dropped to reduce multi-collinearity, and the included year dummy variables have not been included for brevity of presentation, though their sign and significance are discussed in the table footnotes. The dynamic panel estimation procedure was chosen based on statistical properties of the data, namely due to the presence of significant serial correlation, which renders more traditional panel estimation invalid. This is discussed in greater detail in the sections below.

The dynamic modeling with controls for other factors influencing industry development can help us to more aptly consider the influence that state-level energy and environmental policies have on clean technology industry development. Examples include how Renewable Portfolio Standard (RPS) legislation, which requires electricity providers to supply a minimum percentage or amount of customer power from a renewable source, can effect state clean technology employment and innovation. Another example is how cap-and-trade legislation (such as the Regional Greenhouse Gas Initiative among states in the northeast) that uses revenue from sales of emission allowances for investment in energy efficiency can influence clean technology employment and innovation. Public Benefit Funds (PBFs) are another example. PBFs are a pool of resources typically created by levying a small fee or surcharge on customers' electricity rates, which can then be used by states to invest in clean energy supply.

Methodology and Data Sources

The empirical analysis here is exploratory. It is intended to gain some statistical insight about the economic impact of state-level energy and environmental policies and to provide guidance for future research.[5]

There are two state level clean tech industry development indicators of main interest – *clean tech innovation* (as measured by clean tech patenting) and *clean tech employment concentration* (defined as clean tech employment as a percentage of total state employment). For the first indicator – patents -- we consider the influence of state level human capital and venture capital, along with the independent variables of primary consideration here – state level energy and environmental policies. For clean tech employment concentration we attempt to discern the

[5]Full consideration of the economic influence of energy and environmental policy adoption is difficult and beyond the scope of this paper. It requires a variety of types of analyses. A cost-benefit analysis would need to estimate the environmental and health benefits from such policies, which falls in the realm of fields other than industrial economics, as well as an economic valuation to quantify such benefits in pecuniary terms. It also requires some understanding of the short and long term economic consequences of these actions.

effect of specialized and general localized factor conditions -- human capital, innovation/patents, local demand for alternative energy, and venture capital-- together with energy and environmental policies. In the modeling of clean tech employment concentration we also consider energy research and service employment as a dependent variable, to test for the robustness of findings and to examine the scope of employment influenced by the different independent variables under consideration.

The table below provides a detailed description of the variables used.

Dependent Variables[6]	
PEW Clean Tech Employment Concentration	Clean Technology employment as percentage of total employment, measured in natural log. Source Pew Trust (1998-2007). See Appendix A for details.
NETS Clean Tech Employment Concentration	Clean Technology employment as a percentage of total employment, measured in natural log. Based on NETS Establishment data. See Appendix A for details.
Clean Tech Patents	Clean Tech patents per worker, measured in natural log. Source 1790 Analytics for clean patent data and Moody's for total employment (1990-2009)
Independent Variables	
Bachelor's Degree Attainment	Percentage of adults with 4-year college graduates (1990, 1998-2007). Source US Census
High Tech Employment Concentration	High Tech employment concentration. High tech employment as percentage of total state employment. Source Moody's Analytics (1990-2009).
Renewable Energy Use per capita	Renewable Energy Use per Worker, measured in natural log. Source EIA (1990-2009)
Venture Capital Funding per Worker	Venture Capital Funding per Worker, measured in natural log. Source Thomas Reuters (1990-2009)
Energy Policy Category	Energy policies implemented out of eight. Source Pew Center on Global Climate Change
Climate Change Policy Category	Climate policies implemented out of seven. Source Pew Center on Global Climate Change
Transportation Policy Category	Transportation policies implemented out of two. Source Pew Center on Global Climate Change
Building Policy Category	Building policies implemented out of four. Source Pew Center on Global Climate Change
Regional Climate[7] Policy	Regional Climate Initiative
Climate Action Policy	Climate Action Plan
Climate Commissions	Climate Change Commissions and Advisory Groups
GHG Targets	Greenhouse Gas (GHG) Targets
GHG Inventories	GHG Inventory
GHG Registries	GHG Registry

[6]The estimation is constrained by data availability. For example, our main measure of clean tech industry, the Pew Trust defined one, is available for only ten years from 1998-2007.

[7]The regional climate initiative was only enacted in the last year of the sample, in turn a quadratic term for it cannot be included in the regressions and in turn its results should be prospectively interpreted even more tentatively.

State Adoption Plan	State Adaption Plan
Public Benefit Fund	Public Benefit Fund
Renewable Portfolio	Renewable Portfolio Standards
Net Metering Policy	Net Metering
Green Pricing Policy	Green Pricing
Renewable Certificates	Renewable Energy Certificate Tracking System
Energy Efficiency	Energy Efficiency Resource Standard
Green State Gov.	State Government Purchasing Green Power
Vehicle	Vehicle GHG Standards
Bio-Fuels	Mandates and Incentives Promoting Bio-fuels
Green State Buildings	Green Building Standards for State Buildings
Appliance	Appliance Efficiency Standards
Building Codes[8]	Residential and Commercial Building Energy Codes (RBEC and CBEC respectively)
Notes: In the regression results the prefix ln indicates natural log value, lagged followed by suffix # indicates lagged value by # years, term "squared" indicates quadratic of the variable	

The energy and environmental policies fall into 4 main categories – climate change, energy, transportation and building. The policies are described in their categories in the table below with the number of states that have adopted each of the policies in the last column.

[8] Residential and Commercial Building Energy Codes display strong collinearity (state's adopting one very often adopt the other simultaneously) to the point where we can only include one of these in the Arellano-Bond regressions and in turn observe their impact in tandem, since there is not enough variation between the two.

Climate Action	**Regional Initiatives**: Over the past few years, a number of regional initiatives have begun developing systems to reduce carbon dioxide emissions from power plants, increase renewable energy generation, track renewable energy credits, and research and establish baselines for carbon sequestration.	32
	Climate Action Plan (Completed or In Progress): Climate action plans detail steps that the states can take to reduce their contribution to climate change.	36
	Climate Change Commissions and Advisory Groups: States have established advisory boards in order to evaluation the threats and opportunities associated with climate change and mitigation strategies.	23
	GHG Targets: A greenhouse gas emissions target refers to the emission reduction levels that states set out to achieve by a specified time.	20
	GHG Inventory: Greenhouse gas emissions inventories account for all sources of emissions as well as carbon sequestration within the state.	43
	GHG Registry: Many states choose to report their GHG emissions with the Climate Registry. The Climate Registry establishes consistent, transparent standards throughout North America for businesses and governments to calculate, verify and publicly report their carbon footprints in a single, unified registry.	41
	State Adaption Plan: States are recognizing the importance of pre-emptive action to address their vulnerability to climate change and many have begun to address adaptation concerns either within broader state climate action plans, or through separate efforts matching their mitigation activities.	15
Energy Sector	**Carbon Cap/Offset for Power Plants**: Cap and trade ensures that total emissions from all covered entities fall below a cap that typically declines over time.	5
	Public Benefit Fund: Many states have funds, often called "public benefit funds," dedicated to supporting energy efficiency and renewable energy projects. The funds are collected either through a small charge on the bill of every electric customer or through specified contributions from utilities.	25
	Renewable Portfolio Standards: These states have set standards specifying that electric utilities generate a certain amount of electricity from renewable or alternative energy sources.	29
	Net Metering: Net metering is used to measure a customer's total electric consumption against that customer's total on-site electric production. When on-site production exceeds use, the customer can send electricity to the grid and receive payment.	45
	Green Pricing: Green pricing programs allow customers to pay a premium on their electric bill to have a portion or all of their power provided from renewable energy sources.	45
	REC Tracking System: These states have established a central mechanism to track renewable energy credits.	29
	Energy Efficiency Resource Standard: An Energy Efficiency Resource Standard (EERS), Energy Efficiency Portfolio Standard (EEPS), or energy efficiency target is a mechanism to encourage more efficient generation, transmission, and use of electricity and natural gas.	21
	State Government Purchasing Green Power: These state governments purchase all or some portion of their power from renewable energy sources.	17
Transportation	**Vehicle GHG Emissions Standards**: The California Air Resources Board has set a vehicle emissions standard that other states have chosen to adopt. The standard requires that new vehicles, on average, achieve an emissions reduction of 30 percent by 2016 and covers carbon dioxide, methane, nitrous oxide, and hydrofluorocarbon emissions.	17
	Mandates and Incentives Promoting Biofuels: State laws and regulations that promote the use of biofuels may include financial incentives (tax credits, exemptions, grants, loans, funds), vehicle acquisition and fuel use requirements (mandates for public fleets to purchase alternative fuel vehicles), or fuel standards and mandates (low-carbon fuel standards and fuel blend mandates).	39
Buildings	**Green Building Standards for State Buildings**: Many states choose to use LEED certification as the standard of new construction. LEED emphasizes state of the art strategies for sustainable site development, water savings, energy efficiency, materials selection and indoor environmental quality.	29
	Appliance Efficiency Standards: States can set minimum energy efficiency standards for products ranging from light bulbs to refrigerators, but many of these standards have since been preempted by federal standards.	12
	Residential Building Energy Codes: Residential Building Energy Codes establish a minimum level of energy efficiency for residential buildings.	38
	Commercial Building Energy Codes: Commercial Building Energy Codes establish a minimum level of energy efficiency for commercial buildings.	37

The policies that have been adopted most broadly include net metering (45 states), green pricing (45) and greenhouse gas inventories (43). The policies that have been adopted by only a few states include carbon cap and offset for power plants (5) and state adaptation plans (15).

The states leading in policy adoption are California (21 out of 21) and Washington, Oregon, Connecticut and Massachusetts (all with 19). The New England region has two other states -- Vermont and Rhode Island -- among the top 7 states in adopting policies (with 17 each), followed by Maine 14th among states and New Hampshire 22nd. Mississippi (3) and Tennessee and Alabama (4 each) have adopted the fewest energy and environmental policies to address climate change.

In the model specification individual policies for each state are measured as the number of years enacted and as zero if the policy has not been adopted. Most of the policies across the states have been adopted in the past five years. For example in Vermont (one of the most active states) only 5 of the 17 policies that have been adopted were adopted before 2005. This will make it difficult to consider the long-term influence of energy and environmental policies on clean technology development in this empirical exploration.

Modeling Specification and Estimation

The modeling is exploratory and the results are preliminary. Effort is made to not constrain the information in the data and thus allows for varying effects over time and different channels through which clean technology patenting and employment concentration may be impacted by the independent variables. The model estimation is dynamic, examining changes in the variables to account for unobserved state heterogeneity, and includes year dummy variables to control for the business cycle and time trends in overall clean technology industry growth. The modeling also allows for state level energy and environmental policies and human capital/education to have non-linear effects with the inclusion of quadratic terms. This is designed to capture potential increasing or diminishing returns over time.

Patents are likely to have an effect on employment with some time lag. The timing of this transmission is an empirical question and we thus include lagged values of clean tech patents going back several years. The human capital variables are normalized with use of the percentage of the population with a bachelor's degree and also the percentage of employment in high technology as a proxy for technological skill level. The remaining non-policy variables are specified in natural logs and normalized by total employment for ease of interpretation.

Model Estimation Approach

A significant issue for the analysis is that the policy variables may not be exogenous, given that states choose whether or not to adopt policies (i.e., they self-select). It is possible that a contemporaneous correlation between policy adoption and clean tech employment and/or patenting could reflect "reverse causation," in which energy and environmental policies are enacted as a state becomes more intensive in clean tech industry development (biasing the estimates of policy influence upwards) or that policies are enacted when states lag behind in clean tech patents and/or employment (biasing the estimates of policy downward). Similarly, there is likely to be significant unobserved state heterogeneity, the presence of omitted variables which will influence clean tech industry development independent of these policies. To address these concerns we employ the Arellano-Bond dynamic panel estimation.[9] This modeling approach is designed to address potential endogeneity, unobserved state heterogeneity, and other issues which may produce serial correlation in the data, by examining the change in the dependent variables, including a lagged difference of the dependent variable and measuring the independent variables in differences as a form of the instrumental variable approach (see Woolridge 2002). The presence of such serial correlation is consistent with the path dependence implied by the networking effects of the Helpman-Krugman model.

The hypothesis tables (presented in Appendix B) test for serial correlation. The typical AR(1) Arellano Bond regression (which includes one lagged difference of the dependent variable) is valid so long as we fail to reject the second hypothesis of no second order correlation (additional lags are included for the regressions which do not meet this requirement). Rejection of the hypothesis of no first order serial correlation implies that a dynamic panel is required for valid estimation. One of the assumptions of this procedure for estimation is that more temporal observations are included than regressors; however Forbes (2000) argues that the results are still valid even if this assumption is not met.

An implication of dynamic panel estimates are that they do not provide a goodness of fit measure, as the interpretation of the R squared has been distorted since the explanation is being in part provided by lagged value(s) of the dependent variable. For this reason, and also to gain an understanding of the bias involved in standard panel estimation, the fixed effects estimates have been included in Appendix C.

Modeling Results

Clean Technology Innovation: Patents as Dependent Variable Results

Patent Modeling Details

The first of the dependent variables examined is clean technology patenting. We consider empirically the influence of energy and environmental policies, human capital, and venture capital on clean tech patenting. The results are presented in the table below. The first column of the table presents the model results with the human capital measure being the percentage of adults with bachelor's degree (BA) and the second uses high tech employment concentration (HT) as a proxy for human capital. Time dummy variables are also included to capture influences of the business cycle or general industry trends, which may bias the impact of policies due to coincidental timing of adoption. In both models presented here and in all the subsequent model presentation all insignificant quadratic terms from the regression are removed to reduce multicollinearity and to produce more parsimonious models.

[9]In all models, there exists significant serial correlation in the data. Thus standard panel data estimates are invalid, and dynamic panel estimation is required for valid statistical inference. For this reason, the results in the body of this paper focus on the dynamic panel estimates.

a.) Bachelor Degree Attainment Percentage of Adult Population, and b.) High Technology Employment Concentration

In the regression the columns are presented with the BA regressions in the first column and the HT regression in the second column.

Table 1: Arellano-Bond for Clean Patents by individual policy with year DV's[10]

Dependent Variable: **Natural Log of Clean Patents per Worker** **Explanatory Variables**	Model 2a	Model 2b
Lagged Patents	.0508 (0.544)	-.0141 (0.817)
Lagged2 Patents		**-.0678 (0.257)**
Lagged3 Patents		**.1102* (0.098)**
Bachelor's Degrees	**-.0003 (0.114)**	
Regional Climate	**.0053*** (0.004)**	**.0022*** (0.001)**
Climate Action Plans	**-.0007 (0.145**	**-.0010*** (0.000)**
Climate Commissions	**-.0008 (0.296)**	**.0018*** (0.010)**
Ghg targets	-.0004 (0.690)	.0002 (0.771)
Ghg Inventories	**.0008 (0.124)**	**.0006** (0.029)**
Ghg Registeries	-.0019 (0.258)	.0002 (0.774)
State Action Plan	**.0015 (0.711)**	**-.0021** (0.015)**

[10]Time dummy variables were significant and positive in the early 2000's. Highly insignificant quadratics have been excluded from the regressions. All variables with a significant observation have been highlighted in bold. Underneath each coefficient estimate is the p value test of significance, for a null hypothesis that the coefficient equals zero. For ease of interpretation, asterisks (*) have been included to denote the level of significance. One asterisk implies significance at the 10% level, two at the 5% level, and three at the 1% level. Time dummy variables were significant for all years in the BA regressions (all positive). In the HT regressions they were initially positive, becoming insignificant in 2004, and then significant and negative in 2007

Public Benefit Funds	.0004 (0.143)	.0008*** (0.000)
Renewable Portfolio	.0000 (0.937)	-.0003 (0.472)
Net Metering	.0003 (0.334)	.0001 (0.780)
Green Pricing	.0006 (0.417)	.0008* (0.083)
Renewable Certificates	.0044*** (0.000)	.0017*** (0.000)
Energy Efficiency	-.0016*** (0.002)	-.0002 (0.485)
Green State Gov.	.0011 (0.166)	.0003 (0.410)
Vehicle	-.0021* (0.076)	-.0003 (0.790)
Bio-fuels	.0028* (0.065)	.0025** (0.010)
Green State Buildings	-.0008 (0.334)	-.0007 (0.170)
Appliances	.0009 (0.412)	.0010 (0.367)
Building Codes	-.0010 (0.296)	-.0011* (0.086)
Climate Commission Squared		-.0005*** (0.000)
Ghg Inventories Squared	-.0001** (0.032)	-.0000*** (0.005)
Ghg Registeries Squared	.0010*** (0.006)	.0005*** (0.001)
State Action Plan Squared	-.0068** (0.015)	-.0000 (0.993)
Net Metering Squared	-.0001*** (0.000)	-.0001*** (0.000)
Vehicle Squared		-.0007*** (0.002)
Bio-fuel Squared		-.0005*** (0.012)
Green State Squared	.0004** (0.020)	.0002*** (0.002)
Appliance Squared		.0004 (0.113)
Venture Capital	.0001 (0.523)	-.0001 (0.431)
High Tech		.1769** (0.047)

The modeling results suggest that the percentage of adults with bachelor's degree is a poor proxy for clean technology relevant human capital. High technology employment concentration appears to be a more appropriate proxy for clean tech relevant human capital. For this reason, we will focus on the results from the high tech regression. State level high tech employment is one of the largest determinants of clean tech patenting, along with the feedback effect of previous clean tech patenting within a state. This result provides some evidence of a networking effect to clean tech patenting.

In terms of the effect of state-level energy and environmental policies, the magnitude estimates are generally very small. Positive impacts are observed for regional climate initiatives, climate change commissions and advisory groups, public benefit funds, and green building standards for state buildings. Positive returns diminishing over time are identified for greenhouse gas (GHG) inventories and state governments purchasing green power. The results indicate negative effects for climate action plans, state adoption plans, renewable portfolio standards, energy efficiency resource standards, residential building codes, vehicle greenhouse gas standards and net metering (the latter two increasing over time during the sample as seen based on the negative and significant second order of the polynomial).

While certain policies appear to support the first stage of the Porter hypothesis (namely that environmental regulations can spur innovation) in terms of statistical significance, the actual experience suggest very minor benefits in this regard over the shorter term (though again there does appear to be a feedback effects over time to clean tech patenting). Some of the negative results are also quite sensible, in that minimum requirements for vehicle standards and building codes eliminate the viability of possible patents which fall short of these mandates. The results suggest that state adaptation plans and climate action plans have not effectively fostered such innovative activity, and even appear to have decreased it slightly, which might be a consideration for future adoption or alterations of such programs.

Clean Tech Employment Concentration Modeling Results

Clean Tech Employment Concentration Modeling Summary

The second focus of our empirical inquiry examines whether state level energy and environmental policies contribute to clean tech employment concentration. The definition of clean tech industry we employ is from the Pew Trust. It is a widely accepted definition and representative of what is generally thought of as clean tech. This measure thus serves as the primary focus, though we also present and consider energy research and service related employment. We have excluded the high tech measure of human capital from the employment regressions, since it overlaps with the dependent variables, and in turn is endogenous.[11]

In addition to the energy and environmental policies, we include as independent variables in the modeling human capital, venture capital and local demand for renewable energy. Time dummy variables are again included to control for trends in the industry over time and to control for employment trends related to the business cycle. This in conjunction with the Arellano Bond dynamic panel analysis controlling for issues of endogeneity, serial correlation and omitted

[11] Based on the detail of the data, it was not possible to alter the series (removing the overlap) to address this.

variable bias/state heterogeneity are designed to isolate the impact of these policies on clean technology concentration within a state.

) +

Clean Tech Employment Concentration Modeling Results Explanation and Discussion

Table 2: Arellano Bond Results for the Pew definition by individual policy with year DV's[12]

Dependent Variable: **Natural Log of Clean Jobs per worker**	
Explanatory Variables	Model 4
Lagged PEW	.0237 (0.877)
Lagged2 PEW	-.1371 (0.179)
Lagged3 PEW	-.0758 (0.400)
Patents	-.0029 (0.706)
Lagged Patents	-.0007 (0.939)
Lagged2 Patents	-.0018 (0.839)
Lagged3 Patents	.0028 (0.768)
Lagged4 Patents	.0103 (0.276)
Lagged5 Patents	.0152 (0.145)
Lagged6 Patents	.0035 (0.752)
Lagged7 Patents	.0018 (0.882)
Bachelor's Degrees	.0000 (0.313)
Venture Capital	-.0000 (0.332)

[12] A significant (and positive) time dummy variable was found only for 2002. The insignificant policy quadratics have been dropped from the regression.

Renewables	**.0004* (0.061)**
Climate Action	**-.0001** (0.024)**
Climate Commission	.0001 (0.110)
Ghg Targets	-.0001 (0.372)
Ghg Inventories	-.0001 (0.290)
Ghg Registries	-.0001 (0.470)
State Adapt Plan	**.0004** (0.047)**
Public Benefit Funds	-.0001 (0.277)
Renewable Portfolio	**-.0001 (0.128)**
Net Metering	-.0000 (0.802)
Green Pricing	-.0001 (0.435)
Renewable Certificates	.0001 (0.341)
Energy Efficiency	.0002 (0.256)
Green State Gov.	-.0001 (0.100)
Vehicle	-.0000 (0.852)
Bio-fuels	.0000 (0.724)
Green State Buildings	**-.0002** (0.050)**
Appliances	.0001 (0.452)
Building Codes	.0000 (0.819)
Public Benefit Funds Squared	**.0000* (0.059)**
Vehicle Squared	**-.0001* (0.052)**

The results do not support the hypothesis that state-level energy and environmental policies have significant positive effects on clean tech innovation or employment over the shorter term, based on previous experience with such policies. Even when individual policies had statistically significant positive influence, they are of very small magnitude. The interpretation of the dynamic panel results is slightly altered compared to more traditional estimation. Here the coefficient on the policies represents the annual effect on the percentage change in clean technology concentration. Given the annual increase in even the fastest growing states is less than 10%, and thus the coefficient is a magnitude smaller than the standard interpretation, and since even the largest concentration is only 1% of total employment, the job creation directly attributable to the policies is quite minor based on these estimates.

In terms of individual policies, the results suggest small positive impacts on clean tech employment concentration which are increasing over time for public benefit funds and a positive impact of state adaptation plans. Of note, state adaptation plans had an insignificant impact under traditional estimation suggesting a downward endogeneity bias, which could be explained by states tending to put in place these plans because they are lagging behind in clean technology use and employment.

Negative impacts on employment concentration are identified for vehicle greenhouse gas standards, energy efficiency resource standards, and renewable portfolio standards with the former two having increasing negatively effects over time. These results strongly suggest that there may be, at least in the short term, limited clean tech industry development benefits of these policies.

The results of the clean tech patent and Pew defined clean tech employment concentration modeling suggest the importance of differentiating by individual energy and environmental policies, allowing for non-linear effects of policy over time, as well as the importance of addressing or controlling for the fact that states are heterogenous and self-select policies. Another preliminary finding is that the results on employment are less favorable for “command and control” type regulations, which set maximums (for energy use/emissions) or minimums (for alternative energy use) and may not strongly incentivize innovation. The modeling results using energy research and services employment produce similar findings, see below, about the importance of differentiating by policy, and controlling for state heterogeneity and policy endogeneity.

Renewable energy has a significant and positive influence on clean tech employment which is consistent with what would be expected, though the magnitude of the effect is again quite modest. No significant result of patents is identified for the Pew measure of clean tech employment, though it is almost significant at 10% with a five year lag. This finding of a rather weak link between clean patenting and employment is unexpected and inconsistent with much of the research linking patent production and employment growth (Freeman and Soete 1997 also Jorgensen et al. 2007), however clean tech patenting does appear to have a statistically significant and sizable impact on energy research and service employment (see below).

Energy research and service related employment

In addition to the Pew Trust defined industry, we consider an alternative measure in the empirical modeling. The alternative definition is intentionally significantly different than the Pew Trust definition. This enables exploration of how different policies and local factor conditions impact different types of clean tech industries and allows for consideration of the robustness of findings.

The what we call NETS definition, unlike the Pew Trust definition, uses standard industry classification (NAICs) definitions and therefore can be more easily replicated and extended over longer time periods. The NETS clean tech definition is smaller in terms of employment representing just .21 percent of total employment in the U.S, compared to .56% for the Pew definition. It focuses specifically on energy research and services.

Compared with the baseline Pew Trust measure, however, the NETs measure includes a broader range of industries within the energy sector than those only associated directly with clean energy. For the NETs definition we draw on the National Establishment Time-Series (NETS) database that goes up to 2009 and with establishment data provided by Walls &Associates (2010). The largest numbers of establishments are in energy conservation and electrical power generation research and services.

Table 3: Arellano Bond for the Nets definition by Individual Policy[13]

Dependent Variable: **Natural Log of Clean Jobs per Worker**	
Explanatory Variables	model 8
Lagged Nets	**.5129*** (0.000)**
Patents	-4.6709 (0.288)
Lagged Patents	4.3663 (0.328)
Lagged2 Patents	-1.3548 (0.767)
Lagged3 Patents	**13.4314*** (0.006)**
Lagged4 Patents	**8.8381* (0.082)**
Lagged5 Patents	1.9259 (0.735)
Lagged6 Patents	1.0451 (0.846)
Lagged7 Patents	8.4290 (0.123)
Renewables	-.0391 (0.673)
Venture Capital	-.0021 (0.828)
Bachelor's Degrees	-.0066 (0.521)
Climate Action	**-.0528** (0.027)**

14 Time dummy variables were significant and positive in 2000-2002 and 2006. Highly insignificant quadratic terms have been excluded from column 1 and dropped from the regression in column 2.

Climate Commission	-.0768 (0.211)
Ghg Targets	-.0333 (0.530)
Ghg Inventories	**-.1004***** **(0.001)**
Ghg Registries	.0030 (0.953)
State Action	-.1742 (0.108)
Public Benefit Funds	**-.0508***** **(0.001)**
Renewable Portfolio	**-.1009***** **(0.000)**
Net Metering	**.0417**** **(0.016)**
Green Pricing	.0821 (0.135)
Renewable Certificates	**.0624**** **(0.032)**
Energy Efficiency	**.1266***** **(0.000)**
Green State Gov.	.0111 (0.636)
Vehicle	.0712 (0.209)
Bio-fuels	.0230 (0.550)
Green State Buildings	-.0017 (0.963)
Appliances	.0755 (0.202)
Building Codes	-.0241 (0.591)
Regional Climate	**.1800*** **(0.076)**
Ghg Inventories Squared	**.0062***** **(0.001)**
Green Pricing Squared	**-.0322***** **(0.001)**

The magnitudes of the NETs model coefficient estimates are consistently greater than the previous employment definitions, for both the significant positive and negative results. Furthermore, the relatively large and significant lagged value of this measure suggests that there are "networking" or feedback effects to energy research and service related employment.

In terms of energy and environmental policy impact their influence appears to be more significant and positive than for the Pew clean tech industry definition. The primary determinant of energy research and service employment concentration, however, is not energy and environmental policy but state clean tech patenting, with a lag of three, four and possibly up to seven years.
The NETs model identifies positive impacts on energy research and service employment for the energy policies of net metering, energy efficiency resource standards and renewable energy certificates. Positive impacts are also identified for regional climate initiatives (though again this policy in particular has been adopted by states only at the very end of the oberservation time period).

Some individual energy and environmental policies appear to have a negative impact on energy research and services employment. Public benefit funds and renewable portfolio standards appear to have a negative impact on the NETs measure of clean tech employment. The nature of these policies suggests a potential policy implication. Those with a negative impact tend to be more command and control style regulations, mandating minimums for alternative energy use or maximums for emissions. They perhaps can be viewed as impacting the broader energy sector at a fixed costs level, rather than providing incentives on the margin to improve efficiency. This finding seems to warrant further consideration.

Paper Summary and Future Research

The results do <u>not</u> support the hypothesis that state-level energy and environmental policies have significant positive effects on clean tech innovation or employment. Even when individual policies had statistically significant influence the impacts were generally of very small magnitude.

Rejecting a significant short-term influence of state level energy and environmental policies on clean tech employment can be informative to public discourse on the effect of policies on jobs. It can make for more careful and realistic statements and assumptions about the potential short-term clean tech employment impact of energy and environmental policies. Even the states with relatively aggressive energy and environmental policies still have very low concentration in clean tech (less than 1 percent of total employment). This paper does not explore the broader employment impacts of energy and environmental policies.

One of the most significant findings is on the importance importance of addressing policy endogeneity and unobserved state heterogeneity, as the significant presence of serial-correlation in the data can yield misleading results under traditional panel estimation. There is for some policies an upward bias, and for others a downward bias. It appears that sometimes the motivation for policy implementation (self-selection) might be a strong current state position in clean tech and sometimes the motivation might be due to a weak current positioning and the desire to make it stronger. The results also indicate a feedback effect of energy research and services employment and more weakly patent development. This suggests that while the exploratory analysis suggests that the short-term clean tech employment benefits of environmental and energy policies are likely to be over-stated, the returns may build on themselves but only gradually over time.

The variables found to be most positively influencing clean tech development (i.e. our three dependent variable measures) are innovation/patents and skilled work force. Renewable energy use as an independent variable also appears to have a positive influence on clean tech employment concentration. This is consistent with previous findings on the importance of innovation and human capital in the development of newly emerging technology-based industry and with our understanding of clean tech.

Patents are identified as having a positive impact on clean tech industry employment concentration with a lag, and that lag is particularly sizable and significant for energy research and service employment. What this suggests is that policy makers would need to have a long-term outlook to realize significant broader employment benefits from patenting activity resulting from state level energy and environmental policy implementation. It also suggests that in any conclusions we should be cautious about findings regarding the limited potential for clean tech employment generation from energy and environmental policies over longer time horizons. Any conclusion would need to take into consideration the recent implementation of many of the policies and the time required for the policies to have their full effect on employment. In turn, the analysis here is designed only to weigh in on the short-term effects of these policies on clean tech industry development.

It is hoped that this exploratory research can provide some preliminary insights and structure for consideration of the influence of energy and environmental policies, and other factors, on clean tech industry development over time.

Future Research

Continued exploration, updating and refinement of analysis on the impact of energy and environmental policies on clean tech patenting, clean industry employment concentration and total employment can help to inform future state and federal policy. This modeling has allowed for up to seven years of consideration of the transmission between policies and patents and employment. A longer time series sample allowing for observation of the even longer term impacts (beyond a seven year time period) would be of value.

In addition, it would also be useful to incorporate information on the policies enacted in neighboring states and/or nation-wide (perhaps weighted in terms of relative populations and distance), since such policies in a larger base and/or in a neighboring state may provide incentives for further clean tech patent and business development. It could also be useful to consider metropolitan areas as the unit of analysis with state and neighboring state policies as independent variables considered.

And finally an important related inquiry would be to examine the influence of energy and environmental policies on overall state economies, including on total employment, per capita income and gross state product per capita.

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Appendix A: Alternative Definitions of Clean Tech

1) *From PewTrust (2009),* The Clean Energy Economy Report[14]

The clean energy economy is defined as "one that generates jobs, businesses and investments while expanding clean energy production, increasing energy efficiency, reducing greenhouse gas emissions, waste and pollution, and conserving water and other natural resources." Pew partnered with Collaborative Economics (CEI), a public policy research organization, to examine the growth of the clean energy economy in all 50 states.

Counting Jobs and Businesses

The Pew Trust used micro-level establishment data to count businesses that fit their definition, including those that produce/provide products and services that leverage renewable energy sources, conserve energy and natural resources, reduce pollution and recycle waste. PEW utilized multiple sources to construct their database, including advanced Internet search technology.

PEW identified companies receiving venture capital based on information provided by Cleantech Group, LLC, and New Energy Finance. They gathered information from industry associations and green business directories, press coverage, published articles, and government inventive databases for renewable energy programs. PEW also examined the current Standard Industrial Classification (SIC) codes associated with each company and used these to mine the National Establishment Time Series database (NETS) for other similar businesses.

PEW limited its analysis to a set of core companies/jobs within the clean energy economy so that its count would remain conservative. For instance, PEW did not count Google's Sustainability officer in its search because the company's main focus is not aligned with the clean energy economy. Someone charged with "greening" a company's office was not counted.

CEI developed the database and placed businesses into 3 categories: 1) those who's SIC codes are completely part of the clean economy (energy conservation equipment), 2) those who's SIC codes are partially green (electricians), 3) those that are active in some area of the green economy but who's SIC codes represent something much broader than the green economy (commercial nonphysical research).

This process led to two sets of 8 digit codes: 1) SIC codes that were fully part of clean energy economy, 2) SIC codes where portion of business is in clean energy economy. SIC codes in the first category represent 60% of all companies/jobs in this sector.

[14]This is taken from the report's Appendix B: Methodology for Clean Tech definition and data. This provides methodology and source information for clean tech employment, venture capital and some of the paten data used.

Researchers used the NETS database to track trends in business growth from 1998-2007 across all 50 states and DC. They chose NETS since it provides the most detailed set of business unit information necessary to identify business activities in the clean energy economy.

In order to supplement the information provided by NETS, CEI designed the parameters of an internet search infrastructure developed by QL2, a software engineering firm. This platform allowed PEW to more comprehensively mine internet-based sources, link results to NETS and verify information collected. PEW checked each company's website to verify that they are involved in the clean energy economy. If they did not have a website, the business was not counted.

Following collection, a team of analysts manually checked the validity of the 50-state data.

As part of the data mining process, businesses were grouped in 16 segments: energy generation, energy infrastructure, energy storage, energy efficiency, air and environment, recycling and waste, water and wastewater, agriculture, research and advocacy, business services, finance and investment, advanced materials, energy production, clean building, transportation, and manufacturing and industrial. PEW converted these 16 segments into 5 broader categories: clean energy, energy efficiency, environmentally friendly production, conservation/pollution mitigation, training and support. PEW expects these sectors to remain constant, even if specific jobs and businesses change.

Tracking Investments and Patent Registrations

VC investments and patent registrations reveal where innovation is taking place. VC data was provided by Clean Tech Group and was tracked by industry segment. A company called "1790 Analytics" tracked patent registrations from US Patent and Trade Office on a weekly basis. Included patents related to solar, wind, batteries, fuel cells, and hybrid systems. VC and patent data was collected from 1999-2008.

The "NETS" clean tech definition is the smallest in terms of employment. It focuses specifically on energy research and services. Compared with the baseline Pew Trust measure, it includes a broader range of industries within the energy sector than those just associated directly with clean energy. The NETs-based definition draws on the National Establishment Time-Series (NETS) database that goes up to 2009.

Table: NETS-Based Clean Tech Definition: Energy Research and Services

State	SIC8	Industry	Estabs09
MA	87489904	Energy conservation research and services	250
MA	49119902	Generation, electric power	88
CT	87489904	Energy conservation research and services	80
CT	49119902	Generation, electric power	65
MA	87119906	Energy conservation engineering	52
ME	49119902	Generation, electric power	52
MA	52110301	Energy conservation products	48
NH	87489904	Energy conservation research and services	46
ME	87489904	Energy conservation research and services	35
VT	87489904	Energy conservation consultant	35
NH	49119902	Generation, electric power	34
CT	87119906	Energy conservation engineering	32
MA	87110403	Heating and ventilation engineering	26
RI	87489904	Energy conservation consultant	22
CT	52110301	Energy conservation products	21
VT	49119902	Generation, electric power	20
NH	52110301	Energy conservation products	12
ME	87119906	Energy conservation engineering	10

Appendix B: Arellano-Bond Regression Tests for Serial Correlation

Table 1:

```
Arellano-Bond test that average autocovariance in residuals of order 1 is 0:
         H0: no autocorrelation   z =  -5.35   Pr> z = 0.0000
Arellano-Bond test that average autocovariance in residuals of order 2 is 0:
         H0: no autocorrelation   z =  -1.04   Pr> z = 0.2979
```

```
Arellano-Bond test that average autocovariance in residuals of order 1 is 0:
         H0: no autocorrelation   z =  -5.19   Pr> z = 0.0000
Arellano-Bond test that average autocovariance in residuals of order 2 is 0:
         H0: no autocorrelation   z =  -0.01   Pr> z = 0.9884
```

```
Arellano-Bond test that average autocovariance in residuals of order 1 is 0:
         H0: no autocorrelation   z =  -6.40   Pr> z = 0.0000
Arellano-Bond test that average autocovariance in residuals of order 2 is 0:
         H0: no autocorrelation   z =  -1.58   Pr> z = 0.1137
```

```
Arellano-Bond test that average autocovariance in residuals of order 1 is 0:
         H0: no autocorrelation   z =  -6.54   Pr> z = 0.0000
Arellano-Bond test that average autocovariance in residuals of order 2 is 0:
         H0: no autocorrelation   z =  -1.47   Pr> z = 0.1411
```

Table 2:

```
Arellano-Bond test that average autocovariance in residuals of order 1 is 0:
         H0: no autocorrelation   z =  -3.09   Pr> z = 0.0020
Arellano-Bond test that average autocovariance in residuals of order 2 is 0:
         H0: no autocorrelation   z =  -1.86   Pr> z = 0.0634
```

```
Arellano-Bond test that average autocovariance in residuals of order 1 is 0:
         H0: no autocorrelation   z =  -2.43   Pr> z = 0.0149
Arellano-Bond test that average autocovariance in residuals of order 2 is 0:
         H0: no autocorrelation   z =  -1.84   Pr> z = 0.0665
```

Table 3:

```
Arellano Bond test that average autocovariance in residuals of order 1 is 0:
         H0: no autocorrelation   z =  5.02   Pr> z = 0.0000
Arellano Bond test that average autocovariance in residuals of order 2 is 0:
         H0: no autocorrelation   z =  0.57   Pr> z = 0.5715
```

```
Arellano Bond test that average autocovariance in residuals of order 1 is 0:
         H0: no autocorrelation   z =  4.89   Pr> z = 0.0000
Arellano Bond test that average autocovariance in residuals of order 2 is 0:
         H0: no autocorrelation   z =  0.74   Pr> z = 0.4565
```

Appendix C: Fixed Effects Estimates

The clean tech patent modeling below with fixed effects forthe individual policies.

Table: Clean Patents with individual policies[15]

Dependent Variable | **Natural Log of Clean Patents per Worker**		
R squared		
Within	**0.43**	**0.52**
Between	**0.37**	**0.39**
Overall	**0.55**	**0.54**
Bachelor's Degrees	**.0001 (0.640)**	
Venture Capital	.0002 (0.216)	.0002 (0.129)
Regional Climate	**.0010 (0.522)**	**.0009* (0.068)**
Climate Action	**-.0002 (0.283)**	**-.0003** (0.023)**

[15] Time dummy variables were significant from 2000-2004 and 2006 (all positive). Highly insignificant quadratic terms have been excluded from the regressions.

Climate Commission	.0023*** (0.000)	.0037*** (0.000)
Ghg Targets	-.0000 (0.974)	-.0013*** (0.000)
Ghg Inventories	-.0002** (0.050)	.0000 (0.915)
Ghg Registries	.0016** (0.045)	.0007** (0.045)
State Adoption Plan	-.0007 (0.707)	-.0029** (0.030)
Public Benefit Funds	.0012*** (0.000)	.0004*** (0.000)
Renewable Portfolio	.0001 (0.402)	.0003** (0.021)
Net Metering	-.0000 (0.674)	.0002* (0.060)
Green Pricing	.0007* (0.055)	.0012** (0.012)
Renewable Certificates	.0002*** (0.007)	.0003*** (0.000)
Energy Efficiency	-.0025*** (0.001)	-.0013*** (0.002)
Green State Gov.	-.0000 (0.908)	-.0002 (0.182)
Vehicle	-.0017* (0.071)	-.0015*** (0.003)
Bio-fuels	.0007* (0.058)	.0007 (0.106)
Green State Buildings	.0016*** (0.001)	.0010*** (0.000)
Appliances	.0007 (0.426)	.0015*** (0.001)
Residential Building Codes	-.0005 (0.368)	-.0007** (0.038)
Commercial Building Codes	-.0040 (0.331)	-.0020*** (0.003)
Climate Commission Squared		-.0005*** (0.000)
Ghg Targets Squared		.0002 (0.119)
Ghg Inventories Squared		-.0000** (0.037)
State Adoption Plan		.0007* (0.097)
Public Benefit Funds Squared	-.0001*** (0.000)	

Green Pricing Squared		**-.0001*** (0.084)**
Net Metering Squared		**-.0000*** (0.000)**
Energy Efficiency Squared	**.0002** (0.012)**	**.0001*** (0.009)**
High Tech		**.1295*** (0.000)**
Constant	**.00460 (0.105)**	**-.0001 (0.972)**

Table: Pew Trust Definition by Individual Policies. Highly insignificant quadratic terms have been dropped to reduce multicollinearity.[16]

Dependent Variable | **Natural Log Clean Jobs per Worker**	
R Squared	
Within	**0.52**
Between	**0.00**
Overall	**0.01**
Patents	**.0138* (0.077)**
Lagged1 Patents	**.0185** (0.028)**
Lagged2 Patents	.0018 (0.830)
Lagged3 Patents	.0070 (0.450)
Lagged4 Patents	.0005 (0.953)
Lagged5 Patents	.0026 (0.798)
Laggede6 Patents	.0064 (0.508)
Lagged7 Patents	.0112 (0.234)
Renewables	.0001 (0.505)
Venture Capital	**-.0000** (0.058)**
Bachelor's Degrees	**.0003*** (0.001)**

[16] Time dummy variables were significant from 2001-2007

Bachelor's Degrees Squared	**-.0000*** (0.004)**
Regional Climate	**.0007*** (0.000)**
Climate Action Plan	-.0000 (0.589)
Climate Commission	**.0001 (0.149)**
Ghg Targets	**.0003*** (0.006)**
Ghg Inventories	**-.0001*** (0.003)**
Ghg Registries	-.0001 (0.302)
State Adoption Plan	**-.0002 (0.397)**
Public Benefit funds	**.0001** (0.045)**
Renewable Portfolio	**-.0002*** (0.000)**
Net Metering	.0000 (0.526)
Green Pricing	.0000 (0.719)
Renewable Certificates	**-.0002* (0.074)**
Energy Efficiency	-.0000 (0.340)
Green State Gov.	**-.0001* (0.094)**
Vehicle	-.0000 (0.805)
Bio-fuels	**-.0001** (0.013)**
Green State Buildings	**-.0001 (0.108)**
Appliances	.0001 (0.331)
Residential Building Codes	-.0000 (0.464)
Commercial Building Codes	**-.0002 (0.635)**
Ghg Targets Squared	**-.0000 (0.101)**
Ghg Inventory Squared	**.0000** (0.038)**

Renewable Portfolio Squared	**.0000* (0.074)**
Green Pricing Squared	**-.0000** (0.024)**
Net Metering Squared	**.0000*** (0.006)**
Renewable Certificates Squared	**.0000* (0.075)**
Constant	**.0011 (0.331)**

Table: NETS measure with individual policies[17]

Dependent Variable | **Natural Logs of Clean Jobs per Worker**	
R Squared	
Within	**0.51**
Between	**0.00**
Overall	**0.00**
Patents	-1.0123 (0.842)
Lagged1 Patents	7.2705 (0.159)
Lagged2 Patents	.1330 (0.980)
Lagged3 Patents	**10.5998* (0.056)**
Lagged4 Patents	1.5861 (0.763)
Lagged5 Patents	8.7729 (0.167)
Lagged6 Patents	1.2938 (0.830)
Lagged7 Patents	-3.7739 (0.506)
Renewables	.0277 (0.753)
Venture Capital	.0088 (0.450)
Bachelor's Degrees	.0186 (0.694)

[17] The first column included year dummy variables. Only 2002 was significant. It was also positive.

Regional Climate	.0612 (0.582)
Climate Action	.0101 (0.591)
Climate Commission	.0235 (0.716)
Ghg Targets	**-.1649* (0.057)**
Ghg Inventories	-.0139 (0.245)
Ghg Registries	.0209 (0.697)
State Action Plans	**-.2665* (0.051)**
Public Benefit Funds	**-.0490*** (0.000)**
Renewable Portfolio	**-.0453** (0.018)**
Net Metering	**.0586*** (0.000)**
Green Pricing	**-.0588** (0.015)**
Renewable Certificates	**.0473* (0.054)**
Energy Efficiency	**.1045* (0.086)**
Green State Gov.	**-.0563** (0.012)**
Vehicle	**-.1142* (0.088)**
Bio-fuels	**-.1530*** (0.003)**
Green State Buildings	**.0893** (0.021)**
Appliances	-.0590 (0.373)
Residential Building Code	-.0118 (0.727)
Commercial Building Code	.1325 (0.622)
Climate Commissions	-.0242 (0.107)
Ghg Targets Squared	**.0276** (0.028)**
Energy Efficiency Squared	**-.0111* (0.087)**
Vehicle Squared	.0238 (0.157)

Bio-fuels Squared	**|** **|**	**.0159*** **(0.058)**
Constant	| |	.3428 (0.652)