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The Effects of US State-Level Energy and Environmental Policies on Clean Tech Innovation and Employment

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Abstract

This paper explores the influence of US state-level policies meant to address climate change on clean technology industry development. The largest influence of climate change policies is identified as being on energy research employment. Only some policies seem to contribute positively to clean tech employment while other policies appear to discourage employment growth. The magnitudes of the short term effects, even when statistically significant, are modest. Negative impacts on employment are identified for several mandate-oriented, so called command and control, policies including vehicle greenhouse gas standards, energy efficiency resource standards, and renewable portfolio standards with the former two having increasing negative effects over time. The findings suggest that climate change policy advocates should be careful to not assume that there will be positive clean tech employment benefits from state-level energy and environmental policies. Instead, the benefits from these policies may derive primarily from other considerations beyond the scope of this paper, including health and environmental benefits and reduction of dependence on foreign energy sources.

Keywords: clean tech employment, state industry development, dynamic panel estimation, state energy and environmental policies, climate change policy, economic impact

1. Introduction

This paper explores how US state-level energy and environmental policies may influence clean technology (clean tech) industry development. These policies have been justified primarily based on other criteria—including their environmental and health benefits and potential to reduce dependence on imported energy (Lutsey & Sperling, 2008; Rabe, 2008). There is a long tradition however of examining the economic impacts of energy policies. Hudson & Jorgensen (1974) for example provided econometric projections of the consequences for GDP growth from alternative energy tax policies. Nordhaus (2002) meanwhile focuses on the "induced innovation" effects of climate policy. The question of the economic impact of energy policies remains a crucial element of any cost-benefit analysis on the implementation or continuance of these policies.

We focus on two United States (US) state-level clean tech industry development indicators—clean tech patenting, as a proxy for innovation, and clean tech employment concentration (in total and within clean tech employment we consider energy research and related employment). Our main information sources on state climate change policies and clean tech employment data are both from the Pew Center on Global Climate Change (Pew Charitable Trust, 2009; Pew Center on Global Climate Change, 2011). (Note 1)

Following Michael Porter's (1990) competitive advantage framework and diamond model we consider whether state-level climate change policies are contributing to clean tech development in US states. A hypothesized feedback process of industrial development is considered and tested using a dynamic panel estimation.

Simple correlations suggest some relationship between the implementation of US state energy and environmental policies and clean tech employment concentration. Figure 1 identifies the 50 US states' position with regards to the number of state-level energy and environmental policies states have adopted to address climate change (on the horizontal axis) and clean tech employment concentration (the percentage of total employment in clean tech industries, on the vertical axis). The plot depicts a positive correlation between the number of policies implemented and state clean tech employment concentration. Some examples of states where the strongest correlation appears to hold include California, Maine, Massachusetts, Oregon, and Washington as leaders on both clean tech employment concentration and the implementation of energy and environmental policies; conversely Mississippi and Alabama are low on both.

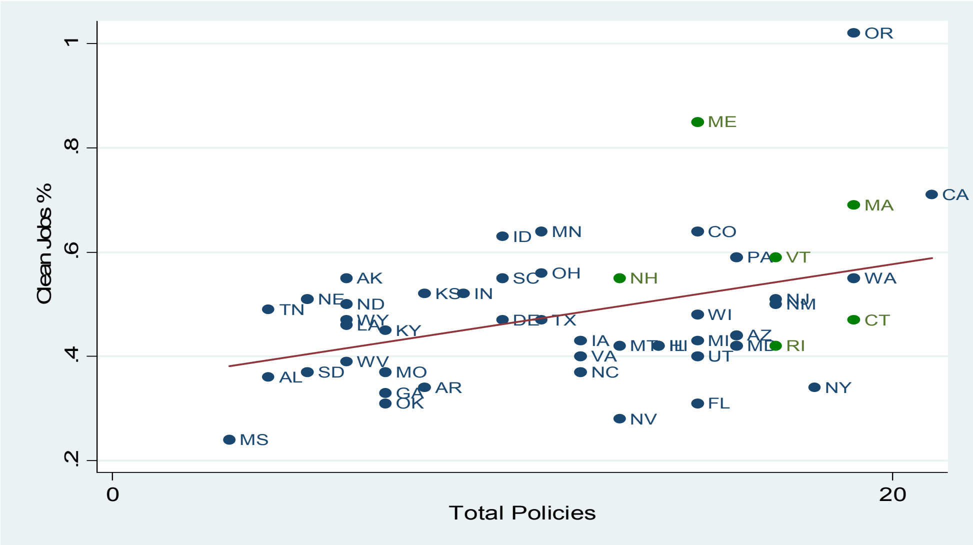

Figure 1. Clean tech job concentration and number of state-level energy and environmental policies

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

Simple correlation, however, cannot be taken for causation. This paper tests econometrically the influence of state energy and environmental policies on state clean tech industry development using detailed policy and economic data over time and across states. In the dynamic panel models, state level policies are quantified individually according to the timing of policy enactment, and tested as explanatory variables with clean tech patenting, clean tech employment concentration and energy research employment as the dependent variables of interest.

The approach used is unique in its consideration empirically of the effects of individual state-level policies over time on an industry's development. The modeling, for example, investigates the contribution to clean tech industry development of Renewable Portfolio Standard (RPS) legislation (which requires electricity providers to supply a minimum percentage or amount of customer power from a renewable source), 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) and Public Benefit Funds (using 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).

1.1 Clean Tech Definition

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) which is commonly referenced and used, see Appendix A for details. 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 sector clean tech is mostly contained within what has been popularly categorized as the "clean" or "green" economy (Muro, Rothwell, & Saha, 2011; UN Division for Sustainable Development, 2012). (Note 2) According to (Muro et al., 2011, p. 19), "(e)ncompassing 2 percent of all positions, the clean economy represents a modest slice of the US economy. Muro et al. add (p. 4) that "(m)ost clean economy jobs reside in mature segments that cover a wide swath of activities including manufacturing and the provision of public services such as wastewater and mass transit. A smaller portion of the clean economy encompasses newer segments that respond to energy-related challenges. These include the solar photovoltaic (PV), wind, fuel cell, smart grid, biofuel, and battery industries." Most clean tech employment is in the newer segments of the clean economy and is more export oriented than the broad clean economy category which includes many local services including recycling and construction. Clean tech is estimated to represent approximately 1/4th of the clean economy. (Note 3) 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.

1.2 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, and 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 and discussion of implications.

1.3 Competitive Advantage Framework

The literature on comparative advantage going back to Ricardo (1891) has been a cornerstone in understanding trade and regional production. Heckscher (1919) and Ohlin (1933) extended the framework of the flow of trade being determined by comparative advantages in productivity by relating productivity to factor endowments (Leamer, 1995). Similarly, the insights of Heckscher & Ohlin have been extended in the new trade theory, primarily associated with the work of Helpman & 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, Ohlin, Helpman, & Krugman, and others, Porter (1990) used his diamond model, see Figure 2, 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.

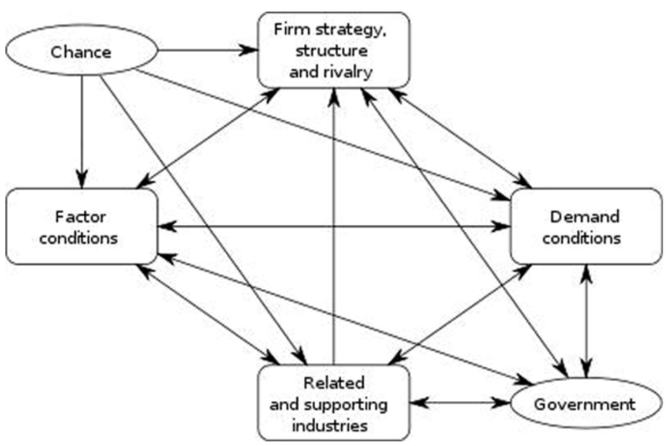

Figure 2. Porter's diamond model of competitive advantage

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 development.

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 & Crean, 2006). A close proximity to sophisticated consumers, according to

Doeringer & Crean, enables the firm to better understand the needs and desires of the customers and gain global competitiveness.

In Porter's competitive advantage framework, state-level energy and environmental policies could be thought of as potential triggers to the emergence of a strong clean tech cluster with exporting companies. 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. A state-level competitive advantage in clean tech industries gained by leadership among states in climate change policy 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. This hypothesized dynamic is considered and tested in the empirical analysis which follows.

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 & Muhlig, 2009; Lampe & Rosegrant, 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 is required (Brenner, 2004).

States can have competitive advantages, according to Porter, 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 considering different definitions and different categories of clean tech. 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, it would be expected that clean tech innovation and employment concentration in state economies will depend on 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 specify draw on this theoretical foundation. The models control for other factors (besides climate change policies) influencing clean industry development. These will be enumerated in the following section.

2. Methodology and Data Sources

The empirical analysis is intended to gain insight about the potential industrial development impact of state-level energy and environmental policies and to provide guidance for future research. 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.

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 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 related 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.

Table 1. Variable descriptions

Dependent Variables	
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.
NAICS Clean Tech Employment Concentration	Clean Technology employment as percentage of total employment. Broader measure using standard industry (NAICS) codes as described in text above, measured in natural log. Source Moody's Analytics (1990-2009). 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 Afor 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 ClimatePolicy	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
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	Residential and Commercial Building Energy Codes (RBEC and CBEC respectively)

Note. 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 by 2009 in the last column.

Table 2. Energy and environmental policies by category and with number of states implementing

Category	Number of states
CLIMATE CHANGE	
1) Regional Initiatives: Multi-state initiatives 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 states
2) Climate Action Plan (Completed or In Progress): Climate action plans detail steps that states can take to reduce their contribution to climate change.	36 states
3) Climate Change Commissions and Advisory Groups: Advisory boards in order to evaluation the threats and opportunities associated with climate change and mitigation strategies.	23 states
4) GHG Targets: A greenhouse gas emissions target refers to the emission reduction levels that states set out to achieve by a specified time.	20 states
5) GHG Inventory: Greenhouse gas emissions inventories account for all sources of emissions as well as carbon sequestration within the state.	43 states
6) GHG Registry: States reporting 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 states
7) State Adaptation Plan: Action plans for states to address their vulnerability to climate change.	15 states
ENERGY	
1) Public Benefit Fund: Public Benefit Funds are 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 states
2) Renewable Portfolio Standards: Standards specifying that electric utilities generate a certain amount of electricity from renewable or alternative energy sources.	29 states
3) 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 states
4) 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 states
5) REC Tracking System: A central mechanism to track renewable energy credits.	29 states
6) 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.	17 states
7) State Government Purchasing Green Power: State governments that purchase all or some portion of their power from renewable energy sources.	17 states
TRANSPORTATION	
1) 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.	39 states
2) 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 states
BUILDING	
Green Building Standards for State Buildings: States that 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 state

2.1 Modeling Specification and Estimation

The modeling allows for state heterogeneity to control for unobserved state specific variation, and includes year dummy variables to control for the business cycle and time trends in overall clean technology industry growth. It 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. We also include lagged values of clean tech patents going back several years. One would presume that patents affect employment with some delay, and the timing of this transmission is an empirical question we examine.

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's influence upwards) or that policies are enacted when states lag behind in clean tech patents and/or employment (biasing the estimates downward). Another significant issue in the analysis is that in the clean tech industry development process, as described above, the various explanatory components are interdependent. To address these concerns we employ the Arellano-Bond (1991) dynamic panel estimation. 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. This modeling approach is designed to address potential endogeneity, and other issues which may produce serial correlation in the data, by 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 is 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.

3. Modeling Results

Clean Technology Innovation: Results with Patents as the Dependent Variable

3.1 Patent Modeling Details

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. 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 table 3 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. In both models presented here and in subsequent models, all insignificant quadratic terms from the regression are removed to reduce multicollinearity and to produce more parsimonious models. The regional climate initiative was only enacted in the last year of the sample. Therefore, its results should be interpreted even more tentatively and a quadratic could not be included.

$$\begin{aligned}&\Delta(Clean\ Patents\ Per\ Worker)\\ &= \alpha + \beta1 * Lagged\Delta(Clean\ Patents\ Per\ Worker) + \beta2 * \Delta(Venture\ Capital) + \beta3\\ &* \Delta(Human\ Capital) + \beta4 * \Delta(Policies) + \beta5 * \Delta(Policies^2) + \beta6\\ &* \Delta(Year\ Dummy\ Variables)\end{aligned}$$

Human Capital is measured as a.) Bachelor Degree Attainment Percentage of Adult Population, and b.) High Technology Employment Concentration

In the regression by individual categories below, the columns are structured with the BA regressions in the first column and the HT regression in the second column.

Table 3. Arellano-Bond for clean patents by individual policy with year DV's

Dependent Variable: Natural Log of Clean Patents per Worker		
Explanatory Variables	Model BA	Model HT
Lagged Patents	.0508	-.0141
	(0.544)	(0.817)
Lagged2 Patents		**-.0678**
		(0.257)
Lagged3 Patents		**.1102***
		(0.098)
Bachelor's Degrees	**-.0003**	
	(0.114)	
Regional Climate	**.0053*****	**.0022*****
	(0.004)	**(0.001)**
Climate Action Plans	**-.0007**	**-.0010*****
	(0.145)	**(0.000)**
Climate Commissions	**-.0008**	**.0018*****
	(0.296)	**(0.010)**
Ghg targets	-.0004	.0002
	(0.690)	(0.771)
Ghg Inventories	**.0008**	**.0006****
	(0.124)	**(0.029)**
Ghg Registeries	-.0019	.0002
	(0.258)	(0.774)
State Action Plan	**.0015**	**-.0021****
	(0.711)	**(0.015)**
Public Benefit Funds	**.0004**	**.0008*****
	(0.143)	**(0.000)**
Renewable Portfolio	**.0000**	**-.0003**
	(0.937)	**(0.472)**
Net Metering	.0003	.0001
	(0.334)	(0.780)
Green Pricing	**.0006**	**.0008***
	(0.417)	**(0.083)**
Renewable Certificates	**.0044*****	**.0017*****
	(0.000)	**(0.000)**
Energy Efficiency	**-.0016*****	**-.0002**
	(0.002)	**(0.485)**
Green State Gov.	**.0011**	**.0003**
	(0.166)	**(0.410)**
Vehicle	**-.0021***	**-.0003**
	(0.076)	**(0.790)**
Bio-fuels	**.0028***	**.0025****
	(0.065)	**(0.010)**
Green State Buildings	**-.0008**	**-.0007**
	(0.334)	**(0.170)**
Appliances	.0009	.0010
	0.412)	(0.367)
Building Codes	**-.0010**	**-.0011***
	(0.296)	**(0.086)**
Climate Commission Squared		**-.0005*****
		(0.000)
Ghg Inventories Squared	**-.0001****	**-.0000*****
	(0.032)	**(0.005)**

Ghg Registeries Squared	**.0010*** **	**.0005*** **
	(0.006)	**(0.001)**
State Action Plan Squared	**-.0068** **	**-.0000**
	(0.015)	**(0.993)**
Net Metering Squared	**-.0001*** **	**-.0001*** **
	(0.000)	**(0.000)**
Vehicle Squared		**-.0007*** **
		(0.002)
Bio-fuel Squared		**-.0005*** **
		(0.012)
Green State Squared	**.0004** **	**.0002*** **
	(0.020)	**(0.002)**
Appliance Squared		.0004
		(0.113)
Venture Capital	.0001	-.0001
	(0.523)	(0.431)
High Tech		**.1769** **
		(0.047)

Note. All variables with a significant coefficient 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.

The level of high technology concentration appears to be a better approximation of clean tech relevant human capital. For this reason, we focus on the results from this regression. State level high tech employment appears to be one of the most significant determinants of clean tech patenting, along with the feedback effect of previous clean tech patenting within a state. In terms of the influence of climate change policies on clean tech patents, the magnitude estimates are generally very small. Positive and sustained 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. While certain policies appear to support the first stage of the Porter hypothesis—that environmental regulations can spur innovation—in terms of statistical significance, these results suggest very minor benefits in this regard over the shorter term, though there does appear to be a feedback effect over time given the significant lag.

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). 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 do indicate that state adaptation plans and climate action plans have not effectively fostered patent innovative activity, and even appear to have decreased it slightly, which raises important considerations of the implications of such programs.

3.2 Clean Tech Employment Concentration Modeling Results

3.2.1 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 first 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 related employment and an alternative narrower definition of clean tech. The high tech measure of human capital from the employment regressions overlaps with the dependent variables, and is therefore endogenous. Based on the level of the data, it was not possible to remove this overlap and so we exclude that variable from the regressions.

In addition to the energy and environmental policies, we include as independent variables human capital, venture capital, and local demand for renewable energy. We also include time dummy variables to control for trends in the industry over time and to control for employment trends related to the business cycle. In conjunction with the Arellano Bond dynamic panel analysis controlling for issues of endogeneity and serial correlation, these are designed to isolate the impact of these policies on clean technology concentration within a state.

$$\Delta(Clean\ Jobs\ per\ Worker) = \propto + \beta1 * Lagged\Delta(Clean\ Jobs\ per\ Worker) + \beta2 * \Delta(Clean\ Patents\ per\ Worker) + \beta3 * Lagged\Delta(Clean\ Patents\ per\ Worker) + \cdots + \beta9 * Lagged7\Delta(Clean\ Patents\ per\ Worker) + \beta10 * \Delta(Renewable\ energy\ use) + \beta11 * \Delta(Bachelor's\ Degrees) + \beta12 * \Delta(Venture\ Capital) + \beta13 * \Delta(Policies) + \beta14 * \Delta(Policies^2) + \beta15 * \Delta(Year\ Dummy\ Variables)$$

3.2.2 Clean Tech Employment Concentration Modeling Results Explanation and Discussion

Table 4. Arellano Bond results for the pew definition by individual policy with year DV's

Dependent Variable: **Natural Log of Clean Jobs per worker** Explanatory Variables			
Lagged PEW	.0237	Ghg	-.0001
	(0.877)	Inventories	(0.290)
Lagged2 PEW	-.1371	Ghg	-.0001
	(0.179)	Registries	(0.470)
Lagged3 PEW	-.0758	**State**	**.0004****
	(0.400)	**Adapt Plan**	**(0.047)**
Patents	-.0029	Public	-.0001
	(0.706)	Benefit Funds	(0.277)
Lagged	-.0007	**Renewable**	**-.0001**
Patents	(0.939)	**Portfolio**	**(0.128)**
Lagged2	-.0018	Net	-.0000
Patents	(0.839)	Metering	(0.802)
Lagged3	.0028	Green	-.0001
Patents	(0.768)	Pricing	(0.435)
Lagged4	.0103	Renewable	.0001
Patents	(0.276)	Certificates	(0.341)
Lagged5	.0152	Energy	.0002
Patents	(0.145)	Efficiency	(0.256)
Lagged6	.0035	Green	-.0001
Patents	(0.752)	State Gov.	(0.100)
Lagged7	**.0018**	Vehicle	-.0000
Patents	**(0.882)**		(0.852)
Bachelor's	.0000	Bio-fuels	.0000
Degrees	(0.313)		(0.724)
Venture	-.0000	**Green State**	**-.0002****
Capital	(0.332)	**Buildings**	**(0.050)**
Renewables	**.0004***	Appliances	.0001
	(0.061)		(0.452)
Climate	**-.0001****	Building	.0000
Action	**(0.024)**	Codes	(0.819)
Climate	.0001	**Public Benefit Funds**	**.0000***
Commission	(0.110)	**Squared**	**(0.059)**
Ghg Targets	-.0001	**Vehicle**	**-.0001***
	(0.372)	**Squared**	**(0.052)**

Note. All variables with a significant coefficient 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. A significant (and positive) time dummy variable was found only for 2002. The insignificant policy quadratics have been dropped from the regression.

For the climate change policies, the results suggest a positive impact of state adaptation plans and a positive effect increasing over time for public benefit funds. Of note, state adaptation plans had an insignificant impact under traditional panel estimation, suggesting a downward endogeneity bias. This could be explained by states tending to put in place adoption plans precisely because they are lagging behind in clean technology use and employment.

The model results suggest the importance of differentiating by individual energy and environmental policies, allowing for non-linear effects of policy over time, and adjustment for the fact that states self-select policies.

Negative impacts on employment concentration are identified for several mandate-oriented, so called command and control, policies including vehicle greenhouse gas standards, energy efficiency resource standards, and renewable portfolio standards, with the former two having increasing negative effects over time.

No significant result of patents is identified for the Pew measure of clean tech employment. This finding is unexpected and inconsistent with much of the research linking patent production and employment growth (Freeman & Soete, 1997; Jorgensen et al., 2007), however clean tech patenting does appear to have a statistically significant and sizable impact on energy research employment (see below).

3.2.3 A Measure of Clean Tech and Energy Research Related Employment

In addition to the Pew Trust defined industry, we consider an alternative definition of clean tech in the empirical modeling. The alternative definition is 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 the findings.

The alternative definition uses standard industry classification (NAICs) definitions and is transparent and therefore can be more easily replicated and extended over longer time periods. In the table below, we compare the U.S. employment concentrations in clean tech (percentages of total employment) to this second measure.

The alternative definition (referred to as the NETS definition) is narrower in terms of employment, representing just .21 percent of total employment in the US. It focuses specifically on energy research and services. Compared with the baseline Pew Trust measure, however, it 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 establishment data provided by Walls & Associates (2010). The largest numbers of establishments are in energy conservation and electrical power generation research and services.

Table 5. Arellano Bond for the nets definition by individual policy

Dependent Variable: **Natural Log of Clean Jobs per Worker** Explanatory Variables			
Lagged Nets	**.5129*****	State	-.1742
	(0.000)	Action	(0.108)
Patents	-4.6709	**Public**	**-.0508*****
	(0.288)	**Benefit Funds**	**(0.001)**
Lagged	4.3663	**Renewable**	**-.1009*****
Patents	(0.328)	**Portfolio**	**(0.000)**
Lagged2	-1.3548	**Net**	**.0417****
Patents	(0.767)	**Metering**	**(0.016)**
Lagged3	**13.4314*****	Green	.0821
Patents	**(0.006)**	Pricing	(0.135)
Lagged4	**8.8381***	**Renewable**	**.0624****
Patents	**(0.082)**	**Certificates**	**(0.032)**
Lagged5	1.9259	**Energy**	**.1266*****
Patents	(0.735)	**Efficiency**	**(0.000)**
Lagged6	1.0451	Green State	.0111
Patents	(0.846)	Gov.	(0.636)
Lagged7	8.4290	Vehicle	.0712
Patents	(0.123)		(0.209)
Renewables	-.0391	Bio-fuels	.0230
	(0.673)		(0.550)
Venture	-.0021	Green State	-.0017
Capital	(0.828)	Buildings	(0.963)
Bachelor’s	-.0066	Appliances	.0755
Degrees	(0.521)		(0.202)
Climate	**-.0528****	Building	-.0241
Action	**(0.027)**	Codes	(0.591)

Climate Commission	-.0768 (0.211)	**Regional Climate**	**.1800*** **(0.076)**
Ghg Targets	-.0333 (0.530)	**Ghg Inventories Squared**	**.0062***** **(0.001)**
Ghg Inventories	**-.1004***** **(0.001)**	**Green Pricing Squared**	**-.0322***** **(0.001)**
Ghg Registries	.0030 (0.953)		

Note. All variables with a significant coefficient 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 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.

There is a positive impact on energy research and service employment of net metering, energy efficiency resource standards, renewable energy certificate policies, and regional climate policies. The primary determinant of energy research and services employment, however, appears to be state clean tech patenting, with a lag of three and four years.

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. This impact diminishes over time for greenhouse gas inventories. Since these policies tend to regulate and add costs to energy, this might be expected. 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 through research. This finding seems to warrant further consideration by policymakers.

The magnitude of the NETs model coefficient estimates is consistently greater than the previous clean tech employment definition, for both the significant positive and negative results. It appears that the energy research and related activities tend to be the most impacted by energy and environmental policies of our clean tech definitions.

4. Summary

This exploratory investigation indicates that US state-level energy and environmental policies have some minor impact on state-level clean tech industry development. Impacts of some climate change policies are identified on both clean tech patenting and clean tech employment concentration, with stronger influence on energy research employment than on clean tech development overall. There is, however, limited support of the hypothesis that a competitive advantage in clean tech industries can be gained by leadership among US states in climate change policies. The findings suggest that climate change policy advocates should be careful to not assume that there will be positive employment benefits from state-level energy and environmental policies. Instead, the benefits from these policies may derive primarily from other considerations beyond the scope of this paper, including health and environmental benefits or a desire to reduce dependence on foreign energy sources.

Negative impacts on employment are identified for several mandate-oriented, so called command and control, policies including vehicle greenhouse gas standards, energy efficiency resource standards, and renewable portfolio standards with the former two having increasing negative effects over time.

Some of the most significant policy impacts identified are with climate change policies promoting energy research employment. There appears to be a feedback mechanism between energy research employment and high tech employment and energy sector patenting. This dynamic warrants further inquiry as the lifespan of these relatively new US state policies extends.

One of the consistent and most important findings is that when assessing policy impacts of climate change policies it is important to differentiate between individual policies and it is also important to allow for non-linear effects over time and to address policy endogeneity. The significant presence of serial-correlation in the data can yield misleading results under traditional panel estimation such as the fixed or random effects. In some instances there appears to be an upward bias, and in others a downward bias. This suggests 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 non-policy variables identified as positively influencing US state-level clean tech development are high tech employment concentration for patenting, renewable energy use for the clean tech employment, and clean tech patenting for energy research employment. This is consistent with previous findings on the importance of innovation and human capital in the development of newly emerging technology-based industries.

The empirical findings regarding climate change policy and clean tech development dynamics have to be qualified. Any conclusion would need to take into consideration the relatively recent implementation of many of the policies and the time required for the policies to have their full effect. Findings should also be qualified by the potentially limited role a single US state, particularly small states, might have on creating a viable market and dynamic for an industry to develop such as clean tech.

4.1 Future Research

Continued exploration and updating of analysis on the impact of US state-level energy and environmental policies on clean tech patenting, and clean industry employment concentration can help to inform future sub-national and national climate change policy and also industry development efforts. This modeling has allowed for up to seven years of consideration of the transmission between patents and employment. A longer time series sample allowing for observation of the even longer term impacts would be of value. Many of these policies had been implemented relatively recently at the time this research began, and the most recent data available then was for the year prior. In a few years, an updated sample may provide not only a longer term estimate of the policies' effects, but also more precise estimates of their shorter term effects.

In addition, it would be useful to incorporate information on the climate change 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 further incentive for clean tech patent and business development in a single state.

Finally, it would also be a worthwhile to extend the analysis to consideration of the influence of state-level energy and environmental policies on the overall economy of states, including total employment, per capita income and gross state product per capita. An international comparison across countries could also be a potentially fruitful avenue of future research.

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References

Allen, C., & Clouth, S. (2012). *A Guidebook to the Green Economy*. UN Division for Sustainable Development.

Arellano, M., & Bond, S. R. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations. *Review of Economic Studies, 58*, 277-297. http://dx.doi.org/10.2307/2297968

Blundell, R., & Bond, S. (1998). Initial Conditions and Moment Restrictions in Dynamic Panel Data Models. *Journal of Econometrics, 87*, 115-143. http://dx.doi.org/10.1016/S0304-4076(98)00009-8

Brenner, T. (2004). *Local Industrial Clusters: Existence, Emergence and Evolution*. London: Routledge. http://dx.doi.org/10.4324/9780203417249

Brenner, T., & Muhlig, A. (2009). Factors and Mechanisms Causing the Emergence of Local Industry Clusters-A Meta Study of 159 Cases. *Papers on Economics & Evolution*, 1-44.

Doeringer, P., & Crean, S. (2006). Can Fashion Save the U.S. Apparel Industry? *Socioeconomic Review, 4*(3), 353-377. http://dx.doi.org/10.1093/ser/mwl04

Forbes, K. J. (2000). A Reassessment of the Relationship between Inequality and Growth. *American Economic Review, 90*(4), 869-887. http://dx.doi.org/10.1257/aer.90.4.869

Gittell, R., & Stillwagon, J. (2011). Tracking Clean Industry Jobs in New England. New England Economic Indicators, New England Public Policy Center, Federal Reserve Bank of Boston, QIII, 4-11, A1-A14.

Heckscher, E. (1919). The Effect of Foreign Trade on the Distribution of Income. *Ekonomisk Tidskrift, XXI*, 497-512. http://dx.doi.org/10.2307/3437610

Helpman, E., & Krugman, P. (1985). *Market Structure and Foreign Trade*. Cambridge: MIT Press.

Hudson, E., & Jorgenson, D. (1974). US Energy Policy and Economic Growth, 1975-2000. *The Bell Journal of Economics and Management Science*, *5*(2), 461-514. http://dx.doi.org/10.2307/3003118

Lampe, D., & Rosengrant, S. (1992). *Route 128: Lessons from Boston's High-Tech Community*. New York City, NY: Basic Books.

Leamer, E. E. (1995). The Heckscher-Ohlin Model in Theory and Practice. *Princeton Studies in International Finance*, No. 77. Princeton, NJ: Princeton University Press.

Lutsey, N., & Sperling, D. (2008). America's bottom-up climate change mitigation policy. *Energy Policy, 36*(2), 673-685. http://dx.doi.org/10.1016/j.enpol.2007.10.018

Muro, M., Rothwell, J., & Devashree, S. (2011). Sizing the Clean Economy: A National and Regional Green Jobs Assessment. The Brookings Institution, Metropolitan Policy Program.

Nordhaus, W. D. (2002). Modeling induced innovation in climate-change policy. *Technological Change and the Environment, 9*, 259-290.

Ohlin, B. (1933). *Interregional and International Trade*. Cambridge, MA: Harvard University Press.

Pew Center for Climate and Energy Solutions. (2011). U.S. Climate Policy Maps. Retrieved from http://www.pewclimate.org/what_s_being_done/in_the_states/state_action_maps.cfm

Pew Charitable Trust. (2009). The Clean Energy Economy. Retrieved from http://www.pewcenteronthestates.org/uploadedFiles/Clean_Economy_Report_Web.pdf

Porter, M. (1990). The Competitive Advantage of Nations. *Harvard Business Review, 68*(2), 73-93. http://dx.doi.org/10.1007/978-1-349-11336-1

Rabe, B. G. (2008). States on Steroids: The Intergovernmental Odyssey of American Climate Policy. *Review of Policy Research, 25*(2), 105-128. http://dx.doi.org/10.1111/j. 1541-1338.2007.00314.x

Ricardo, D. (1891). *Principles of Political Economy and Taxation*. London: G. Bell and Sons Press.

Saxenian, A. L. (1994). *Regional Advantage: Culture and Competition in Silicon Valley and Route* (p. 128). Cambridge, MA: Harvard University Press.

Wooldridge, J. M. (2002). *Econometric Analysis of Cross Section and Panel Data*. Cambridge: MIT Press.

Notes

Note 1. 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*, October 2009, Clean Tech Job Trends, Ron Pernick.

Note 2.
http://www.brookings.edu/~/media/research/files/reports/2011/7/13-clean-economy/0713_clean_economy.pdf

http://www.uncsd2012.org/content/documents/528Green%20Economy%20Guidebook_100912_FINAL.pdf

Note 3. From authors calculations from Muro (2011) et al. Table 1, p. 20, http://www.brookings.edu/~/media/research/files/reports/2011/7/13-clean-economy/0713_clean_economy.pdf

Appendix

Appendix A. Alternative Definitions of Clean Tech

From PewTrust (2009), The Clean Energy Economy Report

The following information 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.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.

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 CleanTech 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 6. Serial correlation tests for Table 3

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 7. Serial correlation tests for Table 4

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 8. Serial correlation tests for Table 5

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 for the individual policies.

Table 9. Clean patents with individual policies

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	.0002
	(0.216)	(0.129)
Regional Climate	**.0010**	**.0009***
	(0.522)	**(0.068)**
Climate Action	**-.0002**	**-.0003****
	(0.283)	**(0.023)**
Climate Commission	**.0023*****	**.0037*****
	(0.000)	**(0.000)**
Ghg Targets	**-.0000**	**-.0013*****
	(0.974)	**(0.000)**
Ghg Inventories	**-.0002****	**.0000**
	(0.050)	**(0.915)**
Ghg Registries	**.0016****	**.0007****
	(0.045)	**(0.045)**
State Adoption Plan	**-.0007**	**-.0029****
	(0.707)	**(0.030)**
Public Benefit Funds	**.0012*****	**.0004*****
	(0.000)	**(0.000)**
Renewable Portfolio	**.0001**	**.0003****
	(0.402)	**(0.021)**
Net Metering	**-.0000**	**.0002***
	(0.674)	**(0.060)**
Green Pricing	**.0007***	**.0012****
	(0.055)	**(0.012)**
Renewable Certificates	**.0002*****	**.0003*****
	(0.007)	**(0.000)**
Energy Efficiency	**-.0025*****	**-.0013*****
	(0.001)	**(0.002)**
Green State Gov.	-.0000	-.0002
	(0.908)	(0.182)
Vehicle	**-.0017***	**-.0015*****
	(0.071)	**(0.003)**
Bio-fuels	**.0007***	**.0007**
	(0.058)	**(0.106)**
Green State Buildings	**.0016*****	**.0010*****
	(0.001)	**(0.000)**
Appliances	**.0007**	**.0015*****
	(0.426)	**(0.001)**
Residential Building Codes	**-.0005**	**-.0007****
	(0.368)	**(0.038)**
Commercial Building Codes	**-.0040**	**-.0020*****
	(0.331)	**(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** **	**.0001*** **
	(0.012)	**(0.009)**
High Tech	**.1295*** **	
	(0.000)	
Constant	**.00460**	**-.0001**
	(0.105)	**(0.972)**

Note. Variables with a significant coefficient 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 from 2000-2004 and 2006 (all positive).

Table 10. Pew trust definition by individual policies (Highly insignificant quadratic terms have been dropped to reduce multicollinearity)

Dependent Variable			
Natural Log Clean Jobs per Worker			
R Squared			
Within	**0.52**		
Between	**0.00**		
Overall	**0.01**		
Patents	**.0138***	**Renewable**	**-.0002*** **
	(0.077)	**Portfolio**	**(0.000)**
Lagged1	**.0185** **	Net	.0000
Patents	**(0.028)**	Metering	(0.526)
Lagged2	.0018	Green	.0000
Patents	(0.830)	Pricing	(0.719)
Lagged3	.0070	**Renewable**	**-.0002***
Patents	(0.450)	**Certificates**	**(0.074)**
Lagged4	.0005	Energy	-.0000
Patents	(0.953)	Efficiency	(0.340)
Lagged5	.0026	**Green State**	**-.0001***
Patents	(0.798)	**Gov.**	**(0.094)**
Laggede6	.0064	Vehicle	-.0000
Patents	(0.508)		(0.805)
Lagged7	.0112	**Bio-fuels**	**-.0001** **
Patents	(0.234)		**(0.013)**
Renewables	.0001	**Green State**	**-.0001**
	(0.505)	**Buildings**	**(0.108)**
Venture	**-.0000** **	Appliances	.0001
Capital	**(0.058)**		**(0.058)**
Bachelor's	**.0003*** **	Residential	-.0000
Degrees	**(0.001)**	Building	**(0.635)**
		Codes	
Bachelor's	**-.0000*** **	**Commercial**	**-.0002**
Degrees	**(0.004)**	**Building**	**(0.635)**
Squared		**Codes**	
Regional	**.0007*** **	**Ghg Targets**	**-.0000**
Climate	**(0.000)**	**Squared**	**(0.101)**
Climate	-.0000	**Ghg**	**.0000** **
Action Plan	(0.589)	**Inventory**	**(0.038)**
		Squared	
Climate	**.0001**	**Renewable**	**.0000***
Commission	**(0.149)**	**Portfolio**	**(0.074)**
		Squared	
Ghg Targets	**.0003*** **	**Green**	**-.0000** **
	(0.006)	**Pricing**	**(0.024)**
		Squared	
Ghg	**-.0001*** **	**Net**	**.0000*** **
Inventories	**(0.003)**	**Metering**	**(0.006)**
		Squared	

Ghg	-.0001	**Renewable**	**.0000***
Registries	(0.302)	**Certificates**	**(0.075)**
		Squared	
State	**-.0002**	**Constant**	**.0011**
Adoption Plan	**(0.397)**		**(0.331)**
Public	**.0001****		
Benefit funds	**(0.045)**		

Note. Variables with a significant coefficient 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.

Table 11. NETS measure with individual policies

Dependent Variable			
Natural Logs of Clean Jobs per Worker			
R Squared			
Within	**0.51**		
Between	**0.00**		
Overall	**0.00**		
Patents	-1.0123	**Renewable**	**-.0453****
	(0.842)	**Portfolio**	**(0.018)**
Lagged1	7.2705	**Net**	**.0586*****
Patents	(0.159)	**Metering**	**(0.000)**
Lagged2	.1330	**Green**	**-.0588****
Patents	(0.980)	**Pricing**	**(0.015)**
Lagged3	**10.5998***	**Renewable**	**.0473***
Patents	**(0.056)**	**Certificates**	**(0.054)**
Lagged4	1.5861	**Energy**	**.1045***
Patents	(0.763)	**Efficiency**	**(0.086)**
Lagged5	8.7729	**Green**	**-.0563****
Patents	(0.167)	**State Gov.**	**(0.012)**
Lagged6	1.2938	**Vehicle**	**-.1142***
Patents	(0.830)		**(0.088)**
Lagged7	-3.7739	**Bio-fuels**	**-.1530*****
Patents	(0.506)		**(0.003)**
Renewables	.0277	**Green State**	**.0893****
	(0.753)	**Buildings**	**(0.021)**
Venture	.0088	Appliances	-.0590
Capital	(0.450)		(0.373)
Bachelor's	.0186	Residential	-.0118
Degrees	(0.694)	Building Code	(0.727)
Regional	.0612	Commercial	.1325
Climate	(0.582)	Building Code	(0.622)
Climate	.0101	Climate	-.0242
Action	(0.591)	Commissions	(0.107)
Climate	.0235	**Ghg Targets**	**.0276****
Commission	(0.716)	**Squared**	**(0.028)**
Ghg Targets	**-.1649***	**Energy**	**-.0111***
	(0.057)	**Efficiency**	**(0.087)**
		Squared	
Ghg	-.0139	Vehicle	.0238
Inventories	(0.245)	Squared	(0.157)
Ghg	.0209	**Bio-fuels**	**.0159***
Registries	(0.697)	**Squared**	**(0.058)**
State Action	**-.2665***	Constant	.3428
Plans	**(0.051)**		(0.652)
Public	**-.0490*****		
Benefit Funds	**(0.000)**		

Note. Variables with a significant coefficient 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.The first column included year dummy variables. Only 2002 was significant. It was also positive.