

The Impact of Private Interest Contributions on Energy Policy Making.

Steffen Jenner ^a, Lotte Ovaere ^b, Stephan Schindele ^c

^a University of Tuebingen, Melanchthonstrasse 36, 72074 Tuebingen, Germany,
steffen.jenner@uni-tuebingen.de, +49-7071-29-72927.

^b Katholieke Universiteit Leuven, Oude Markt 13, Bus 5005 3000 Leuven, Belgium,
lotte.ovaere@econ.kuleuven.be, +32-163-26637.

^c Fraunhofer Institute for Solar Energy Systems, Heidenhofstr. 2, 79110 Freiburg, Germany,
stephan.schindele@ise.fraunhofer.de, +49-761-458-85961.

Abstract: In the last two decades, many U.S. states introduced support policies to promote electricity generation from renewable energy sources. Renewable portfolio standards (RPS) are considered to be the key policy tool to date. This paper tackles the question why some state legislators were front-running the trend of RPS implementation while others adopted policies just recently, and again others have not adopted them so far. In short, what drives states to support renewable energy?

We base our empirical analysis on theoretical reasoning. First, we present an application of the common agency model developed by Dixit et al. (1997) to better understand the impact of special industrial interests on policy decision-making. Second, we compile data on financial contributions of conventional energy interests (CEI) and renewable energy interests (REI) to state-level policymakers between 1998 and 2010. Third, in a series of hazard and tobit regressions, we test the *ceteris paribus* effect of these financial contributions on (i) the probability of a state to adopt a RPS policy and (ii) on the stringency of the RPS. We also control for state effects, time trends, and a set of socio-economic and political covariates.

Combining our empirical framework with the theoretical model produces insights into U.S. state level energy policy making. First, CEI have donated more to state-level legislators affiliated with the Republican Party than to Democrats while contributions from REI went largely to the latter. Second, we reveal statistically significant links between the likelihood of RPS adoption and private interest contributions. Financial contributions from CEI have a negative effect on the likelihood of RPS adoption while REI contributions have a positive effect. Third, the estimates show a similar – albeit less significant – pattern on RPS stringency.

Keywords: Renewable Portfolio Standards, Public Choice Model, Hazard Regression Model, Tobit Regression Model.

JEL Classification: C41, H23, H71, Q48

Acknowledgements: The authors would like to thank Stephen Ansolabehere, William Clark, Richard Freeman, Jens Hainmueller, Aoife Haney, Stef Proost, Richard Schmalensee, Eva Schmid, Josef Schmid, James Snyder, Dustin Tingley, Eicke Weber, Gerhard Willeke, and Daniel Ziblatt for their valuable comments that substantially improved this article. Support from the KUL Energy Institute, the Friedrich-Ebert-Foundation and the Fraunhofer ISE is gratefully acknowledged. The views expressed have not been endorsed by the sponsoring agencies. Any remaining errors, omissions, or inconsistencies are the authors' alone.

1. Introduction

In the last two decades, many U.S. states introduced support policies to promote electricity generation from renewable energy sources (RES-E). Renewable portfolio standards (RPS) are considered to be the key policy tool to date.

A RPS policy requires utilities to produce a certain fraction, or “quota” of their total electricity supply from renewable energy sources. Most legislation allows trading of renewable energy certificates (REC) in state or in larger REC-markets. Thus, utilities can either buy RES-E directly from RES-E producers or they compensate non-compliance of the quota by trading REC. Most RPS policies include penalties to incentivize compliance.

To date, 29 states employ a mandatory RPS while 7 other states have a voluntary RPS in place. Table 1 shows the timeline of RPS implementation from 1996 to 2010. In 1996 only three states had implemented an RPS. In 2010, 36 states supported RES-E generation by means of RPS policies.

Table 1 - Years of RPS policy enactment at the U.S. state level from 1996 to 2010

								CO			IL	MI		
								HI			NC	MO		
AZ	MA	CT						MD	DE		NH	OH		
IA	ME	PA	NJ			CA		NY	MT	ND	OR	SD	KS	
MN	NV	WI	TX			NM		RI	VT	WA	VA	UT	WV	OK
<1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010

Mandatory RPS (standard); voluntary RPS (*italic*), Source: DSIRE (2012).

This paper tackles the question why some state legislators were front-running the trend while others adopted policies just recently, and again others have not adopted RPS policies.

Previous studies shed light on an array of driving factors: geography (solar radiation, available land area, wind speed, conventional energy reserves etc.), economics (unemployment rate, disposable personal income, electricity price etc.), environmental protection (non-attainment area, critical air pollutants, greenhouse gas (GHG) emissions etc.), population (population size, educational level, citizens’ environmental preferences etc.), politics (party ideology, governorship, state-to-state-learning etc.) and private interest (renewable energy interest groups, conventional energy interest groups, environmentalist groups, farmer lobbies etc.). Schmalensee (2011) nicely summarizes the political reasons to support renewables as energy security, green growth, and climate change.

We would like to amend the discourse by introducing a theory-based explanation and a rigorous econometric quantification of the impact of special industrial interest on state level energy policy-making.

The remainder of this article is structured as follows. Section 2 reviews the literature. Section 3 presents our application of the Dixit et al. (1997) agency model. Section 4 develops the covariate and provides the empirical framework. Section 5 presents and discusses the results. Section 6 concludes.

2. Literature Review

For our theoretical model we draw upon literature that studies why certain (inefficient) economic policies are selected as a result of the political process of lobbying (see Persson and Tabellini (2000) for a survey). The concept of interest groups as a possible reason for policy bias has been introduced by Olson (1965), and has proven to be a major contribution to the traditional public choice literature. The author states that groups that have overcome the collective action problem - and thus have organized themselves - have more impact on policy than non-organized groups. This idea has been formalized in a growing literature on lobbying. An extensive overview on lobbying literature is found in Rodrik (1995) and Austen-Smith (1997).

When several lobby groups, often with conflicting preferences, are affected by the action of a particular individual, the principal-agent interaction is formalized as a common agency model. In these models, special interest groups offer transferable utility (e.g. bribes, campaign contributions) to a government agent. In equilibrium, the agent efficiently aggregates the competing principals' influences, absent transaction costs. Common agency models have been widely used to model political distortions in domains such as public finance (Dixit et al. 1997) and environmental policy making (Aidt 1998).

Concerning the empirical part of our paper, there is a lively discourse of econometric studies that assess the motivations of renewable energy support policies. Knittel's (2006) applies a hazard model to the U.S. states sample. He finds that residential wealth, a proxy for residential interest group activity, correlates positively with the adoption of electricity market regulation. Lower levels of residential electricity penetration rates and lower electricity capacity also increase the likelihood of regulation.

Huang et al. (2007) also run a logistic model on the U.S. states. Their results show that states with relatively high gross states products are more likely to implement a RPS. The probability of adoption also increases with population growth and the level of education of citizens. A RPS is less likely to be adopted if Republicans are holding a majority in state house and senate. High expenditure on conservation efforts of natural resources is also associated with lower RPS probabilities.

Chandler (2009) specializes in inter-state learning. His major contribution is to show that states are more likely to adopt RPS policies (and other renewable energy policies) if neighboring states have a RPS in place already. He conclusively argues that policies can diffuse across state borders even when the political environment is ideologically distanced. Chandler (2009) also finds that wealth, measured by personal disposable income, is another driver of RPS adoption.

Lyon and Yin (2010) build on the previous studies. They use a proportional hazard model like Knittel (2006) did and the dependent variable from Huang et al. (2007). In addition, they add variables that account for wind, biomass, and solar potentials. Lyon and Yin (2010) find that the unemployment rate and the percentage of natural gas generation have a negative impact on the odds of RPS adoption. In contrast, the existence of a staffed state chapter of the American Solar Energy Society (ASES), the percentage of Democrats in state legislation and a restructured electricity market elevate the likelihood of RPS adoption. Large wind and large solar potentials also make policymakers more willing to introduce a RPS.

Lyon and Yin (2010) are the first study that links interest groups to the likelihood of RPS adoption. However, they quantify the impact of an interest group only by means of a binary code for the presence of a ASES state chapter. Furthermore, Lyon and Yin (2010) only capture the solar lobby, represented by the ASES. The solar lobby, however, is a weak proxy for renewable energy interest groups since RPS policies favor more price competitive RES-E sources such as wind and biomass. Therefore, the ASES may not even have an interest in the adoption of a RPS since solar photovoltaic and solar thermal technologies may not be used to meet the RPS quota. Finally, Lyon and Yin (2010) miss out on the opposing site of the game. Conventional energy producers are affected by the introduction of a RPS and thus lobby against it.

Delmas et al. (2011) is the most recent study on the U.S. sample. In a logistic model, they find that wind resources, solar resources, LCV Score, democrats in state legislation, income per capita, and the existence of state ASES chapters increase the probability of RPS adoption. Thus they also measure interest group influence by a dummy variable.

Jenner et al. (2012) were the first to apply this question to RES-E policy making at the EU country level. They find that the existence of solar industry associations has a positive effect on the willingness of policymakers to adopt feed-in-tariffs (FiT). By means of technology-specific tailoring of tariff size and contract duration, FiT policies support technologies at different levels of market competitiveness. In other words, solar energy, being rather expensive to produce, is supported by many FiT policies (Groba et al. 2011). In turn, solar associations have an interest in the introduction of FiT policies. However, Jenner et al. (2012) capture the impact of interest groups by a dummy that neglects the heterogeneity between interest groups, states and years.

3. Theoretical model

In our theoretical model, we apply the common agency model (Dixit et al., 1997) to the electricity market. We use the model to study the impact of special interests on the level of support for renewable energy. Campaign contributions offered by the special interests create a political distortion, as the electorally motivated government agent exchanges these contributions for certain political favors. We proceed to show that campaign contributions are an important source of inefficiencies in support policies for renewable energy.

3.1. The Economy

We develop a stylized partial equilibrium model for a large, open economy, with two productive sectors: electricity (x) and a numéraire (y), and a distribution sector (D). Electricity is produced in two subsectors, one using fossil fuels (F) and the other using renewables (R) as energy input (both traded at the world market). In order to support the renewables reaching grid parity, a renewable portfolio standard is introduced in the electricity sector. We define α ($0 \leq \alpha \leq 1$) as the annual RPS fraction (or quota). Thus, for each unit of electricity generated, $\alpha/(1-\alpha)$ certificates (REC) have to be provided. The REC price (p_c) is determined on the REC market. It is partly determined by the

target fraction (α).¹ REC prices rise with increased RPS stringency if we assume that the current existing RES-E capacity does not meet (α). Per unit of output sold, the RES-E producers receive the price of electricity on the market, plus an additional compensation for the certificates. We treat this compensation as a subsidy equivalent.²

Production in the numéraire sector is driven by a CRS technology that only uses labor (l) as input factor. Labor mobility across sectors and profit maximization pin down the wage in the economy to $w=l$. Both the conventional and the renewable energy utility use three inputs: labor, industry specific capital in fixed supply (k) and energy inputs (f, r). Production is described by a neoclassical production function with constant returns to scale. Both electricity subsectors supply electricity in a competitive market. We have the following restricted profit function for the conventional producers: $\pi^F(Q, w, c)$, where Q is the wholesale electricity price and c the world market price for fossil fuels. The profit function is strictly convex and we have $\pi_Q^F > 0, \pi_c^F < 0$. The profit function for the renewables producers is $\pi^R(Q, w, g, \alpha, p_c)$, with g the world market price for renewables. Profits are strictly convex, and we have $\pi_Q^R > 0, \pi_g^R < 0, \pi_\alpha^R > 0$ and $\pi_{p_c}^R > 0$. As levelized costs of RES-E generation exceed the levelized costs of electricity generation from conventional sources, we assume that $g > c$.³ The distribution sector buys electricity from both producers, and sells it on to the end-user as a homogenous product, in a competitive market. The distributing companies are obliged to provide the fraction α of RES-E, which increases their costs. The distributor uses two input factors: labor and capital. The strictly convex profit function is: $\pi^D(P, Q, w, \alpha, p_c)$, with $\pi_Q^D < 0, \pi_P^D > 0, \pi_\alpha^D < 0$ and $\pi_{p_c}^D < 0$. The combination of the competitive setting in the distribution sector and the RPS obligation results in a wedge between the wholesale and the retail price: the consumer pays a mark-up for electricity compared to a situation in absence of a RPS. We have that $P = Q + \alpha p_c$. Consequently, demand for electricity is lower with an RPS obligation.

The economy has N consumers, who derive utility from consuming electricity (x) and the numéraire (y), and disutility from GHG and criteria air pollutants emitted by the conventional energy sector.⁴ The magnitude of these marginal emissions is fixed at a constant rate (ε). Total emissions from the conventional energy sector are: $E = \varepsilon f$.

We define the harm caused by pollution as an increasing and convex function of total emissions: $H(E)$. We assume the utility of a consumer to be quasi-linear and

¹ The scope of the scheme, the renewable technologies participating, and the price caps also affect the certificate price.

² Assuming the RPS is mandatory, the subsidy equals the additional cost of RES-E production relative to conventional electricity production.

³ This is mainly due to renewables' higher intermittency, higher specific upfront costs, lower overall load factor, additional transmissions costs, etc.

⁴ Acknowledging the broad spectrum of additional positive and negative externalities, for simplicity reasons, we limit our model to emissions. Further externalities such as energy security, the impact on job creation and job destruction, volatility and size of electricity prices, impacts in trade, etc. would only multiply the magnitude of our coefficients. Thus, our findings give a valid insight into the direction of the impact. The actual size of the impact is probably even higher than our conservative estimates though.

additively separable, we have: $U_h = y + u(x) - H(E)$, with $u' > 0$, $u'' < 0$. Each consumer receives an income from two sources. For in-elastically supplying her endowment of labor, l_h , to the competitive labor market she gets a wage in return: wl_h . Profits of the electricity sector are in hands of the consumers, who each own a share, $\sigma_{h,i}$, of specific capital in sector i ($i = R, F, D$).⁵ If we maximize utility subject to income, electricity price, and electricity production levels, we can derive the demand for electricity: $D(P)$, with $D'(P) < 0$. Demand for the numéraire is defined as follows: $D(p_y) = I - PD(P)$. If we assume that $D(p_y) > 0$, the wage rate is well defined. We have the following indirect utility function for consumer h :

$$V^h(P, Q, c, g, \alpha, p_c) = l_h + \sigma_{h,F} \pi^F(Q, c) + \sigma_{h,R} \pi^R(Q, g, \alpha, p_c) + \sigma_{h,D} \pi^D(Q, P, \alpha, p_c) + u(D(P)) - PD(P) - H(E) \quad (1)$$

Assuming an additive utilitarian social welfare function, we have:

$$SW(P, Q, c, g, \alpha, p_c) = L + \pi^F(Q, c) + \pi^R(Q, g, \alpha, p_c) + \pi^D(Q, P, \alpha, p_c) + N[u(D(P)) - PD(P)] - NH(E) \quad (2)$$

3.2. The Political Process

We consider a policymaker who must decide on whether or not to install a RPS in a certain year. The policymaker also sets the level of a RPS. The politician decides upon the optimal level of RES-E in the state economy in a given year, α^* . If the existing level of RES-E capacity (β) is smaller than α^* the politician will adopt a RPS.⁶ If $\alpha^* < \beta$ the politician will presumably not install a RPS. We model the decision making process on the optimal level of α as a common agency problem as did Dixit et al. (1997). The policymaker cares about social welfare, and collects private financial contributions during campaigning for office and the time being in office. These contributions will be used later on in an election, which is not modeled (cf. Aidt, 1998). The private industrial interests possibly affected by a RPS are willing to offer these contributions to influence the choice of the policymaker.⁷

We consider functionally specialized interest groups, in the sense that they only care for one specific objective (cf. Aidt 1998). In our model, we allow for conventional energy interests (CEI) and renewable energy interests (REI). That means contributions from CEI (REI) represent a signal to the policymaker in support (opposition) of the adoption of a RPS if the state has not previously adopted a RPS. If a RPS is enacted already, contributions from CEI (REI) represent a signal to the policymaker in support (opposition) of increased stringency of the RPS.

⁵ Human capital, e.g. entrepreneurial skills: only useful in a specific sector (cf. Aidt 1998).

⁶ This level is given in our model, and depends on, amongst others, the level of natural resources in the economy, other support systems like tax cuts etc. $\beta > 0$ indicates that renewable electricity production is viable, even without the support of a RPS.

⁷ The private industrial interests are not necessarily collectively (e.g. industrial association, pressure group) organized; a 'group' can also consist of one individual. The connecting element lies in the shared target of supporting or opposing the adoption of a RPS.

We study the interaction between these private industrial interests and the politician in a policy game that has two stages. In the first stage, each interest group non-cooperatively and simultaneously presents a binding contribution schedule. In the second stage, the politician chooses the level of RPS (α) so as to maximize a weighted sum of social welfare and the preferences of the private industrial interests that are represented by the contributions. This is because he wants to be re-elected, and the probability of re-election partly depends on aggregate campaign contributions and on social welfare. In other words, the policymaker is sensitive not only to the social welfare but also to financial contributions. Thus, the overall welfare maximization yields:

$$W_p(\alpha) = \lambda SW(\alpha) + (1 - \lambda) \sum_l \gamma_l C_l(\alpha) \quad (3)$$

where C_l represents the contributions from the special interests ($l = CEI, REI$). The weight λ ($0 \leq \lambda \leq 1$) represents the policymaker's benevolence towards the social welfare; the adverse $(1 - \lambda)$ thus represents the benevolence towards the private industrial interests. The weights γ_l represent the relative influence of CEI vs. REI on the government. We assume $\gamma_l \in \{0, 1\}$ and $\sum_l \gamma_l \leq 1$. This parameter represents the result of the competition (not modeled) between the two groups, as well as the preference of the policymaker towards either one of the interest group types. The weights are exogenous in our model and will remain exogenous in the empirical analysis as well. We focus on the outcome instead.

The equilibrium of the game is a sub-game-perfect Nash equilibrium in the contribution schedules and the chosen RPS policy. The derivation of the equilibrium in differentiable strategies follows Grossman and Helpman (1994) and Dixit (1996) and is left out. In addition, for simplicity, we only consider those equilibriums in truthful contribution schedules (cf. Aidt, 1998 and Persson and Tabellini, 2000).⁸ As a result, we can write the objective function of the policymaker as:

$$W_p(\alpha) = \lambda SW(\alpha) + (1 - \lambda) \sum_l \gamma_l W_l(\alpha) \quad (4)$$

where W_l is the welfare of l : *CEI*, *REI*. The welfare function of the REI group (and thus its contribution schedule) is the sum of the objective functions of consumers that favor renewable energy, renewable energy producers, and environmentalist groups. The welfare function is defined as:

$$W_R(\alpha) = \sum_{h \in REI} \sigma_{h,R} \tau^R - s_R NH(E) \quad (5)$$

where s_R is the share of this group in the population. This welfare function represents the preferences of the median consumer with renewable energy interests. As we do not model the organization process of special interests, we can consider this welfare function as if it were that of one group. The CEI group is interested in maximizing the

⁸ A globally truthful contribution schedule of an interest group everywhere reflects the true preferences of an interest group (cf. Aidt 1998). This means that the contributions schedule equals the welfare of the interest group, minus a constant that distributes the rent between the politician and the interest group (we set this constant equal to zero – all rent goes to politician).

profit of the conventional energy sector. Their welfare function is the sum of the objective functions of all conventional energy producers and pro-resource development groups that favor conventional energy. The welfare function is defined as:

$$W_F(\alpha) = \sum_{h \in CEI} \sigma_{h,F} \pi^F \quad (6)$$

This welfare function represents the preferences of the median consumer with conventional energy interests. As we do not model the organization process of special interests, we can consider this welfare function as if it were that of one group.

If the policymaker is entirely benevolent to social welfare, the optimal level of α maximizes social welfare, i.e. α is at a level that balances social and private benefits and costs of RPS. The benevolent politician maximizes social welfare as defined in the welfare function. Solving the first order condition leads to an implicit solution for the politically optimal level of α , which we label as α^* . The details of the calculations are provided in the Appendices 8.1. The policymaker compares this level of α^* to the existing level of RES-E capacity (β), and will decide to support RES-E through a RPS if $\alpha^* > \beta$. The objective function of the policymaker who is not only sensitive to social welfare but also to contributions is:

$$\max_{\alpha} W_p(\alpha) = \lambda SW(\alpha) + (1 - \lambda) [\gamma_R W_R(\alpha) + \gamma_F W_F(\alpha)] \quad (7)$$

Straightforward, the optimal level of α now also depends on the relative size of the CEI and REI contributions, on the benevolence balance of the policymaker and on the relative assertiveness of CEI and REI on the decision making process. To study the effect of contributions from REI, we consider the following maximization issue for the policymaker:

$$\max_{\alpha} W_p(\alpha) = \lambda SW(\alpha) + (1 - \lambda) \left[\sum_{h \in REI} \sigma_{h,R} \pi^R - s_R NH(E) \right] \quad (8)$$

The policymaker will no longer opt for the socially efficient level α^* . We find that the optimal support level for the RPS policy in this case, which we define as α^R , exceeds α^* (see Appendices 8.1). The politician compares the level of α again to the existing capacity β to decide whether or not to support RES-E. As $\alpha^R > \alpha^*$, the chance of the policymaker supporting RES-E increases in the presence of renewable energy interests. The effect of contributions from CEI is determined by the following objective function of the policymaker:

$$\max_{\alpha} W_p(\alpha) = \lambda SW(\alpha) + (1 - \lambda) \left[\sum_{h \in CEI} \sigma_{h,F} \pi^F \right] \quad (9)$$

Again, the socially efficient level α^* will no longer be chosen in the presence of private interests. In this scenario, the politician opts for a level α^F that is lower than α^* (see Appendices 8.1). The politician compares the level of α again to the existing capacity β to decide whether or not to support RES-E. As $\alpha^F < \alpha^*$, the chance of the policymaker supporting RES-E decreases in the presence of conventional special interests.

Applying the well-established Dixit et al. (1997) common agency model to the electricity market allows us to model how campaign contributions are an important source of inefficiencies in the support for renewable energy. The next section will test the core hypothesis that policymakers are sensitive to CEI and REI contributions. We assume that CEI contributions have a negative effect on the probability of RPS adoption and on the stringency of the RPS while REI contributions come with positive impacts.

4. Empirical Framework and Data

From Section 3 we know that policymakers are responsive to the maximization of social welfare and possibly to private interest contributions. Our empirical analysis tests the hypothesis that policymakers actually respond to private interests in renewable energy policy making. We measure the impact of private interest with a covariate that captures financial contributions from CEI and REI respectively.

4.1. Dependent Variable

In the subsequent empirical analysis, we will work with two different dependent variables. *RPS Binary* is a binary variable that indicates whether a RPS is enacted (1) or not (0). *ISI* is the *incremental share indicator (ISI)* from Yin and Powers (2010). The *ISI* represents “the mandated increase in renewable generation in terms of the percentage of all generation” (Yin and Powers, 2010: 1142). Thus, the *ISI* is a metric of the stringency of RPS schemes. The *ISI* is constructed as

$$ISI_{it} = \frac{\eta_{it}^{RES} * \kappa_{it}^{RES} * q_{it}^{total} - Q_{it}^{RES}}{q_{it}^{RES}} \quad (10)$$

with η_{it}^{RES} representing the yearly fraction as a percentage of RES-E to total electricity generation; κ_{it}^{RES} representing the percentage of RES-E generation capacity that is legally eligible to meet η_{it}^{RES} ; q_{it}^{total} indicating the annual total electricity generation; and Q_{it}^{RES} indicating the absolute RES-E generation capacity from previous years. We use *RPS Binary* in the proportional hazard model and the *ISI* in the tobit model.

4.2. Independent Variables

Previous studies have mostly relied on binary codes that equal 1/0 if an interest group does/does not exist in the particular state i in the given year t (Delmas et al., 2011; Jenner et al., 2012; Lyon and Yin, 2010). We argue that this approach neglects the important heterogeneity between different interests that results from differences in the magnitude of their contributions. In other words, “money matters”. The more financial “fire power” an industrial interest can spend, the better its chances to have an impact on the decision-making process.

We measure the amount of annual contributions that have been made to politicians at the U.S. state level between 1998 and 2010. Data on the individual contributions has kindly been provided by the *National Institute on Money in State Politics* (NIMSP), a non-partisan, non-profit organization (visit their outstanding webpage at FollowTheMoney.org). Their dataset contains contributions to U.S. state

level policymakers from 1989 to 2011. The data is comprehensive for all 50 U.S. states in 1998 and afterwards.

From the total amount of individual contributions we filtered 473,747 contributions that came from conventional and renewable energy industries as well as pressure groups that are closely related to energy and/ or environmental issues. These interest groups would be affected directly by the introduction of a RPS. We distinguish between branches we assume to favor the introduction of a RPS, e.g. alternative energy producers and environmental protection groups; and groups we expect to favor to not have a RPS adopted, e.g. oil, natural gas and coal related industries and pro-resource development groups.

We assume contributions from conventional energy interests (we referred to them in Section 3 as “CEI”) to have a negative impact on the probability of a policymakers to adopt a RPS while the aggregated contributions from the group of renewable energy interest (“REI”) have a positive influence on the odds of adoption. Furthermore, we assume that CEI (REI) contributions have a positive (negative) effect on policy stringency. Figure 1 presents the development of CEI and REI contributions (in absolute terms) as an aggregate of all U.S. state level contributions from 1998 to 2010 (NMISP 2011).

Figure 1 – CEI and REI Contributions at the U.S. state level from 1998 to 2010

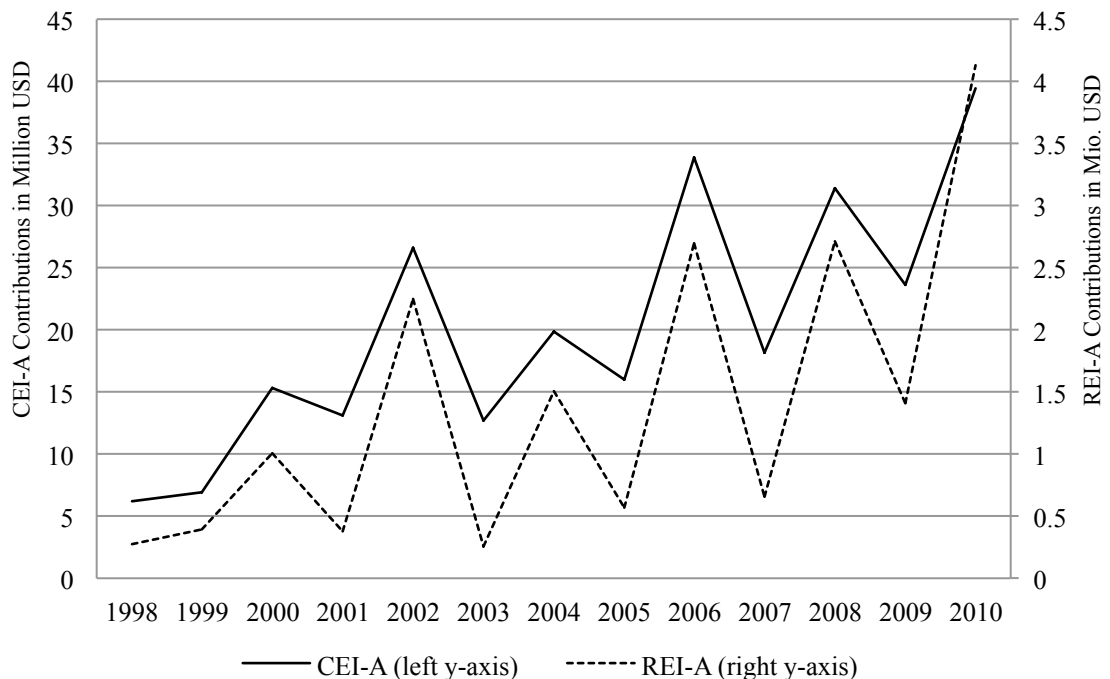
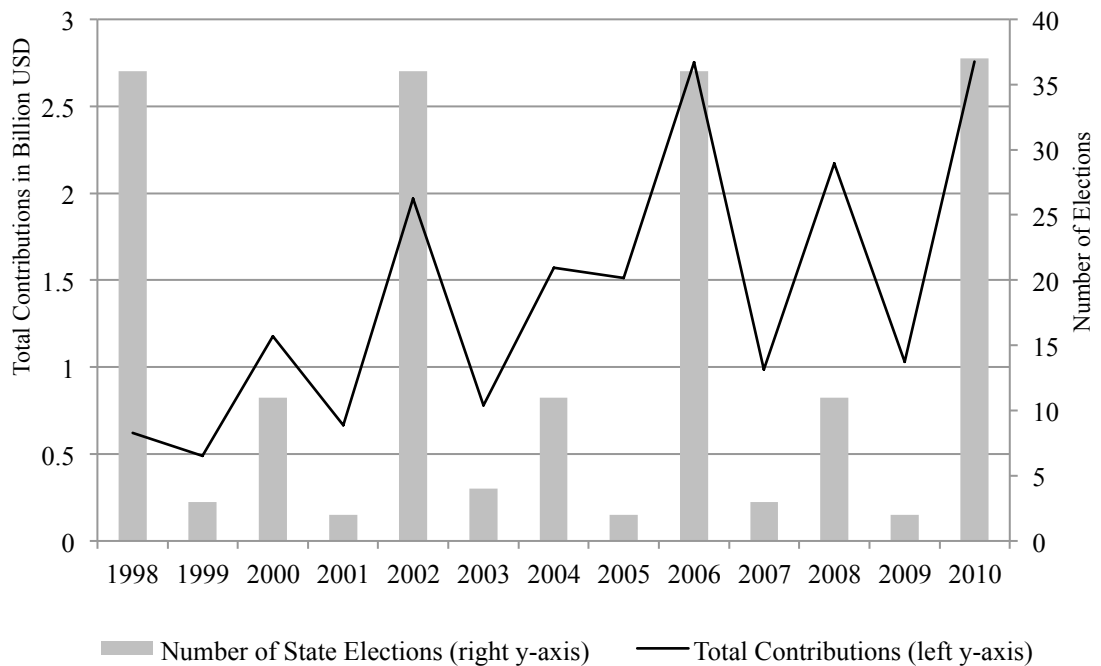


Figure 1 shows that both REI and CEI contributions fluctuate and increase over time. The fluctuations can be explained by frequency of state level elections. Thus, Figure 2 presents the years with gubernatorial elections (NCSL2011) and the total amount of contributions (NMISP 2011).

Figure 2 – Total Contributions and Elections at the U.S. state level



Since the number of elections correlated with both total and energy sector contributions, using the ratios of CEI and REI to total contributions is the best way to accurately capture the impact of contributions. Ratios also help to control for the inflation that affects both energy sector contributions and total contributions. In our regressions, we use three kinds of covariates: Absolute contributions *CEI-A* and *REI-A*, and the ratio of these contributions to the total contributions *CEI-R* and *REI-R*. We also test a series of interaction terms.

4.3.Controls

Multiple aspects can determine the enactment and stringency of a policy. Our major interest is to find out to what extent private interest contributions drive these decisions. However, other variables also factor in the ultimate decision about policy enactment and policy stringency.

Republican Governor (GOV-R) and *Republicans in State Legislature (LEG-R)*. Party theory argues that the ideological background has an impact on policymakers' decisions. The adoption of a renewable energy support scheme such as an RPS is a major decision in favor of state intervention into the electricity market. Following Lyon and Yin (2010) and Huang et al. (2007), we assume that Republican governors and Republicans in state legislature are more reluctant to introduce RPS schemes. The mean voting score published by the League of Conservation Voters (LCV) also shows that Democrats vote approximately 10 times more often in favor of environmental and climate policies than Republicans at the state level. *GOV-R* is a binary code that equals "1" if the governor is affiliated with the Republican Party and "0" if the governor is a Democrat. *LEG-R* represents the percentage of Republican members of the state houses and senates. The variables are correlated. Thus we use *GOV-R* in our main model and *LEG-R* in robustness checks. We will also use party affiliation of the governor as an interaction term with our *CEI-R* and *REI-R* covariates.

Public Opinion (PUB-R). Party affiliation is only one side of the story since there is considerable ideological cross-state heterogeneity within a party. For instance, Republican politicians in New England states tend to take more liberal or democratic positions than their colleagues in the Southern States. Similar to Lyon and Yin (2010), we capture the general political position of a state by the percentage of persons that describes themselves as “Republicans”.

Neighboring states with RPS (N-RPS). The federalist political system of the U.S. fosters state-to-state learning. In the RPS case the diffusion of policies across neighboring states is of particular importance because regional renewable electricity certificate (REC) markets incentivize the adoption of RPS systems in recent years if neighboring states already institutionalized a REC market. Chandler (2009) found that the share of neighboring states that have a RPS in place positively affects the likelihood of adoption. We include Chandler’s variable and assume its coefficient will also be positive.

State Income (INC) and *Energy Sector Employment (E-EMPL)*. Public interest theory argues that policymakers are sensitive to the wealth of their constituents. Since the adoption of a RPS scheme brings energy capacities online that would not be price competitive in the absence of the policy, additional costs emerge. Utilities will forward these costs to the end-user. Policymakers in relatively poor states may be less willing to advocate the additional burden that comes from a RPS than policymakers in wealthier states. Knittel (2006) and Huang et al. (2007) found such a link. Therefore, *INC* represents the median income of a 4-person household. The share of mining and utility sector employment in total employment, *E-EMPL*, follows a similar rational. We expect policymaker in states with high mining and utility sector employment to be less motivated to adopt a RPS that could threaten these jobs.

Non-Attainment Area Index (NAA). Public health benefits from the replacement of conventional energy sources by renewable energy sources because their generation produces less toxic air pollutants and emissions. Lyon and Yin (2010) and Chandler (2009) found that policymakers in states where many people live in so-called non-attainment areas are more likely to support a RPS. Therefore, we include the EPA (2011) data for local air pollutants per 2000 population. The ratio represents the level of exposure to critical air pollutants. *NAA* presumably increases the odds of RPS adoption.

RES-E Capacity (RES-CAP). Existing renewable energy capacities make it easier for policymakers to support RES-E generation. One rational is that these technologies have already proven their market competitiveness. Another rational is that RPS can protect existing RES-E to stay in the market even when unconventional energy sources such as shale gas enter the market. Following Lyon and Yin (2010) we include the percentage of non-hydro RES-E in total electricity capacity. The variable is used in models with *RPS Binary* as the dependent variable. We drop *RES-CAP* if *ISI* is the dependent variable because, by design, the former is endogenous to the latter.

Lobby Regulation Index (REG). The effectiveness of private interest groups to influence the decision making process is also affected by the receptiveness of the political system itself. Newmark (2005) constructed a lobby regulation index that captures the number of lobby regulations at the state level. We took the 2003 score of this index which means the variable is time invariant. Controlling for the variable may result in lower coefficients for the other covariates because these kind of fixed effects take out parts of the distribution of the dependent variables. Thus we interact *REG* with the *CEI-R* and *REI-R* covariates.

In a series of robustness checks we also tested a couple of additional control variables such as the percentage of GDP that is contributed by the energy and mining industries, greenhouse gas emissions per capita, population growth, solar irradiation and others. We do not include these controls because they are highly collinear with other variables and thus would have likely biased the estimates.

4.4.Data

We compiled 1998-2010 panel data on RPS policies, the contributions, and most of the control variables for the U.S. states sample without D.C. Data has been compiled from the EIA (2011), EPA (2011), DSIRE (2012), BLS (2011), BEA (2011), and NCSL (2011). The public opinion dataset is a private data set from Harvard University. It ranges to 2006. Thus we limited the empirical framework to 2006. If comprehensive public opinion data is available in the future, we can easily extend the dataset by four years. In Table 2, the summary statistics of the dataset are presented.

Table 2 – Summary Statistics

	Obs.	Mean	Std. Dev.	Min	Max	Unit	Source
RPS Binary	650	0.15	0.36	0	1	Binary	NMISP (2011)
ISI	650	1.16	4.46	0	32.10	%	NMISP (2011)
REI-A	650	28.05	79.89	0	839.60	\$1,000	NMISP (2011)
CEI-A	650	404.95	917.91	0	11144.14	\$1,000	NMISP (2011)
REI-R	650	0.02	0.07	0	1.55	%	NMISP (2011)
CEI-R	650	0.27	2.61	0	41.72	%	NMISP (2011)
GOV-R	650	0.52	0.50	0	1	Binary	NCSL (2011)
PUB-R	450	38.48	8.57	0	73.68	%	private
N-RPS	650	25.09	28.39	0	100.00	%	DSIRE (2012)
INC	650	51.73	7.84	35.58	73.60	\$1,000	BEA (2011)
E-EMPL	650	1.16	1.33	0	9.29	%	BLS (2011)
NAA	650	0.36	0.58	0	2.41	%	EPA (2011)
RES-CAP	650	4.12	4.94	0	27.59	%	EIA (2011)
LEG-R	650	47.91	15.07	10	89.00	%	NCSL (2011)
REG	650	10.34	3.12	1	17.00	Index	Newmark (2005)

4.5.Model Specification

As outlined above, we are working with a balanced panel data set of 50 U.S. states across 9 years. We first run a series of times series cross sectional regression on the base of ordinary least square (OLS) estimations. OLS results are provided in the Appendices 8.2. Comparing the model determination of a random effects model with a fixed effects model, a Hausman (1978) test rejects the null hypothesis. Thus, we incorporate state fixed effects to take time-invariant biases such as the institutional environment or the RES-E potential out of the error term. We also induce dummy variables for all but one year. These time effects control for federal economic and policy impacts that are invariant to states. The model specification is written as:

$$DV_{it} = \alpha + \beta_1 CEI_{it}^R + \beta_2 REI_{it}^R + \beta_X Z_{it} + \gamma_1 \mu_i + \gamma_2 \mu_t + \varepsilon_{it} \quad (11)$$

where Z_{it} is a suite of our controls; μ_i , μ_t represent the fixed effects; and ε_{it} is an error term. DV_{it} takes the form of either *RPS Binary* or *ISI*. In some specifications, CEI^R and REI^R are replaced with CEI^A and REI^A or interaction terms.

However, the OLS model is inappropriate to answer our research questions. With regard to the first question, ordinary least square (OLS) and weighted least square (WLS) regressions are not applicable because of the non-linear nature of the dependent binary response variable, *RPS Binary* (Wooldridge 2002). Furthermore, we are actually only interested in the state-years prior to the enactment of a RPS since we want to estimate the factors that lead up to the decision. Thus, the beta parameters are biased by state-years after the policy has been enacted. It is also important to exclude state-years after policy adoption because RPS policies may have an effect on the contributions of interest groups, i.e. the independent variable may well be endogenous to the dependent variable after it turns "1".

With regard to the second question, the OLS estimators will be screwed because of the left-tailed distribution of the *ISI*. The *ISI* contains so-called corner solutions only. That means the *ISI* values are strictly positive and the distribution contains many zeros. Thus the distribution fails to meet the Gauss-Markov normality assumption that is crucial to OLS regressions. As a result, the t-statistics and p-values would be invalid.

The use of maximum likelihood estimation (MLE) is more appropriate in cases of non-linear regression functions (Wooldridge 2002). In the following, we elaborate on two MLE models, a hazard model (Kiefer 1988) that is commonly applied in labor market economics and public health and a tobit model. The literature also discusses other MLE models, such as Poisson, censored, and truncated models. However, Poisson models are not useful in our case because they require the dependent variable to be a count not a binary variable (*RPS Binary*) or a left-tailed level variable (*ISI*). Censored and truncated models specialize on samples with missing data or distributions that lack a part of the population. Both events do not occur in our case.

4.5.1. Hazard Model

With regard to the hazard model, the dependent variable is defined as the conditional probability $P_1 = P(t, X, Z)$ of a state to adopt regulation in a certain year, given the state did not adopt such regulation before: $P_0 = 1 - P(t, X, Z)$ (Jenkins 1995). The model drops the state-years in the first year after policy enactment to specifically address our first question of what drives states to adopt a RPS. The logit model allows transferring the coefficients into odd ratios. Thus, the model estimates the relative effect of a mean unit change on the probability of a state adopting a RPS in year t given that the state has not adopted a RPS before. The logit specification is written as follows:

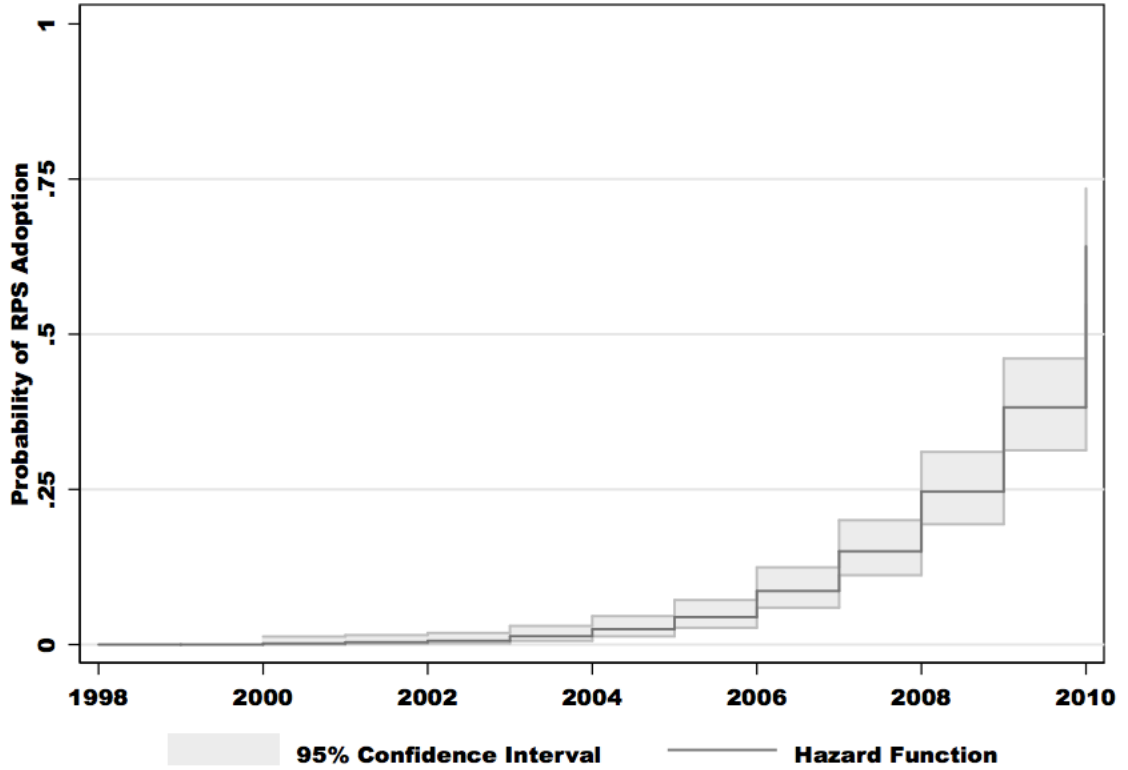
$$\text{logit} \left\{ PR(P_1 / P_0) \right\} = \lambda_0(t) + \beta_1 CEI_{it}^R + \beta_2 REI_{it}^R + \beta' Z_{it} + \varsigma_i + \varepsilon_{it} \quad (12)$$

where $\lambda_0(t)$ is the baseline hazard of RPS adoption only determined by time; CEI and REI are the contribution ratios; Z_{it} is a suite of political, energy, environmental, and socio-economic controls expected to have an impact on RPS adoption; ς_i is the state-specific random-intercept that covers the otherwise omitted time-constant state impacts that cause some states to generally be more likely to adopt RPS schemes than others; ε_{it} is the error term. β_x is the slope estimator that measures the predicted change in the probability of RPS adoption when the variable x increases by 1 unit, everything else held fixed.

Figure 3 presents the Kaplan-Meier hazard function. The exponential slope of the curve illustrates the increasing willingness of policymakers across states to adopt

RPS policies. In 2010, the curve ends at 72%. The remaining 28% represent the 14 states that have not yet implemented a RPS (see Table 1).

Figure 3 – Kaplan-Meier Hazard Function



4.5.2. Tobit Model

In order to analyze the effect of the covariates on the policy stringency after the RPS has been enrolled; we apply a tobit regression model to the state-years that have been dropped by the hazard model. It allows using a stringent metric, the *ISI* (Yin and Powers 2010), as the dependent variable. The reason for applying a tobit model lies in the fact that the *ISI* has a lower corner solution of zero. Thus the *ISI* distribution is strongly left-tailed and the values are strictly non-negative. The tobit function can be written as

$$ISI_{it} = \lambda_0(t) + \beta_1 CEI_{it}^R + \beta_2 REI_{it}^R + \beta' Z_{it} + \varsigma_i + \varepsilon_{it} \quad (13)$$

as specified for the logit regression.

4.5.3. Endogeneity

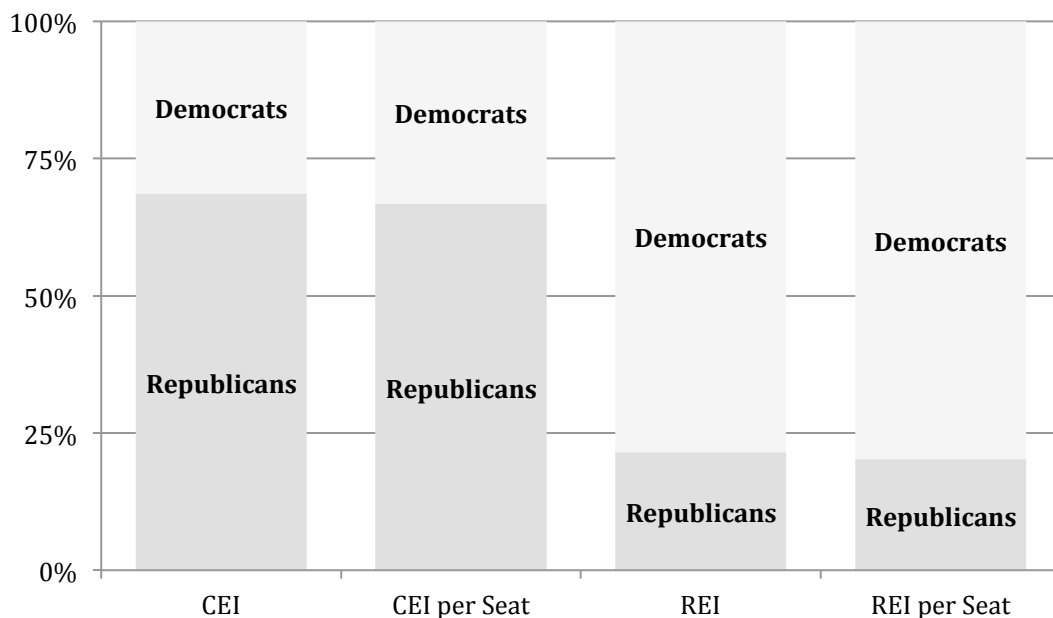
This kind of econometric data analysis is commonly scrutinized with regard to the endogeneity issue. The claim is that an omitted variable is hidden in the error term that does not only correlate with the dependent variable but also with one of the independent variables. In other words, the estimation could neglect the impact of an underlying variable that drives both the likelihood of RPS adoption and the amount of the contributions. If such an unobserved factor is part of the error term, the post-estimation statistics are invalid. Furthermore, such correlation would raise doubt about whether the estimation can identify causal impacts (Wooldridge 2002).

The best option to defend the analysis against such claims would be to conduct an experiment. For instance, one could hand out financial contributions to a randomly selected group of policymakers and evaluate if they react differently than a control group of policymakers that have not received the money. Such a design would neither be financially feasible for us nor democratically defensible in general. Thus, we are left with two rather conservative measures to defend the study against the endogeneity claim. First, in all our estimations we find that the correlation between the residuals and the contribution variable is <0.1 . Thus, the correlation between the error term and the independent variable of our interest is very low. As a consequence, we argue that even if the error term hides an unobserved factor that varies across the observations, it only affects the overall likelihood of RPS adoption and not the amount of contributions. Second, we interpret that estimation as carefully and as conservatively as possible. Thus, if the coefficient is not statistically significant at the 1% level, we do not refer to percentage values for interpretation.

5. Empirical Findings

A glance at the descriptive statistics provides insight into the recipients of the contributions. Figure 4 shows a simple two-party comparison of the 1998-2010 aggregate of CEI-A and REI-A contributions. CEI have donated two to three time more state-level legislators affiliated with the Republican Party than to Democrats. In contrast, REI contributions to Democrats are roughly three times higher than to Republicans. This pattern holds true in absolute and per seat terms. We will use interaction terms and control variables to capture this party-bias.

Figure 4 – Absolute CEI and REI contributions to Republicans and Democrats



This imbalance verifies the hypothesis that private industrial contributions tend to be donated to likeminded politicians. The LCV score showed that Democrats are more likely to endorse renewable energy and climate policies than Republicans. REI contributors appear to anticipate this bias. As a consequence, they support Democrats to much larger extents than Republicans. The same logic holds true for CEI contributors and Republicans. Since Republicans are generally more likely to oppose environmental regulation, indicated by a low mean LCV score, CEI contributors support them in their

stance against market intervention. Both findings come without much surprise. However, it shows that we need to control for party bias, and it verifies that party affiliation is a major driver of contributions in the first place.

5.1. What Drives the Adoption of a RPS?

Table 3 presents the results of the proportional hazard model. The estimation investigates the drivers of policy adoption as considered in the first research question. Absolute contributions do not relate significantly to *RPS Binary*. We argued above that state characteristics such as the size or gubernatorial elections impact absolute values and we should thus use ratios.

The ratios *REI-R* and *CEI-R* verify our initial theoretical hypothesis. *REI-R* has a positive impact on the probability of RPS adoption while *CEI-R* has a negative impact. More specifically, an increase of *REI-R* by one standard deviation increases the probability of RPS adoption by 65%, everything else held fixed. An increase of *CEI-R* by one standard deviation decreases the odds of RPS adoption by 33%. Both links are significant at the 1% level.

Referring to our theoretical assumptions, we argue that policymakers are sensitive to private interest contributions. They anticipate that REI benefit from a RPS while CEI prefer to keep conventional energy capacities online. Thus, policymakers factor the relative contributions of CEI and REI into their decision making. They are less willing to adopt a RPS if CEI contributions are high. In contrast, they endorse such policy if REI contributions are high. Of course, other aspects also determine the ultimate decision and we will discuss them next.

The *GOV-D* and *GOV-R* interaction terms reveal an interesting pattern. First, *REI-R* has a significant positive (64%) effect on the odds if there is a democratic governor in office. In other words, REI contributions work if there is a presumably likeminded (see LCV Score discussion above) governor in office. However, if the governor is a Republican, he or she can veto the adoption of a RPS. That may explain why *REI-R* spending does not have a significant effect on RPS adoption if a Republican is governor. Another reason can be that Democrats receive significant REI contributions (see Figure 3) while the amount that is donated to Republicans is just too small.

Second, *CEI-R* has a significant negative (-24%) effect on RPS adoption if the governor is a Democrat and a significant negative (-100%) effect on RPS adoption if the governor is a Republican. Therefore, CEI contributions decrease the likelihood of RPS adoption regardless of the party affiliation of the governor. However, the effect of *CEI-R* is much larger if there is a Republican in office than if a Democrat is governor. In other words, CEI contributions demotivate politician across the spectrum to adopt a RPS. CEI contributions to politicians in states with a Republican governor seem to be especially effective.

The *REG* interaction terms show that the level of lobby regulation as quantified by Newmark's (2005) index, does not largely affect the size of the coefficients. A technical reason is that *REG* vary across states only. Nevertheless, this model receives the lowest AIC and BIC scores among all models. These scores show that interacting the *REG* variable with the CEI and REI contributions increases the overall fit of the model. The *REG* variable thus captures otherwise omitted state specific characteristics that are not captured by the state clusters already. A polity reason can be that the

number of lobby regulations does not largely decrease the effectiveness of CEI and REI lobbying.

Table 3 – Hazard Model Results – Beta parameters and Odd-Ratios

	RPS Binary							
	(H_B_1)		(H_B_2)		(H_B_3)		(H_B_4)	
	beta	OR	beta	OR	beta	OR	beta	OR
REI-A	0.097 (0.094)	10%						
CEI-A	-0.135 (0.222)	-13%						
REI-R			0.499*** (0.178)	65%				
CEI-R			-0.408*** (0.151)	-33%				
REI-R x GOV-D					0.492*** (0.162)	64%		
CEI-R x GOV-D					-0.281*** (0.095)	-24%		
REI-R x GOV-R					-0.069 (0.149)	-7%		
CEI-R x GOV-R					-7.698* (4.451)	-100%		
REI-R x REG							0.450*** (0.139)	57%
CEI-R x REG							-0.423*** (0.136)	-34%
GOV-R	-0.647 (0.449)	-48%	-0.658 (0.462)	-48%	-0.210 (0.600)	-19%	-0.656 (0.457)	-48%
PUB-R	-5.047** (2.188)	-99%	-5.115** (2.065)	-99%	-4.946** (2.295)	-99%	-5.019** (2.071)	-99%
N-RPS	-0.400 (0.384)	-33%	-0.416 (0.378)	-34%	-0.437 (0.385)	-35%	-0.382 (0.383)	-32%
INC	-0.455 (4.692)	-37%	-0.129 (4.573)	-12%	0.001 (4.736)	0%	0.093 (4.661)	10%
E-EMPL	-0.668 (0.890)	-49%	-0.701 (0.928)	-50%	-0.380 (0.806)	-32%	-0.604 (0.864)	-45%
NAA	0.720*** (0.263)	106%	0.748*** (0.250)	111%	0.682*** (0.253)	98%	0.758*** (0.260)	113%
RES-CAP	-0.131 (0.272)	-12%	-0.144 (0.289)	-13%	-0.144 (0.270)	-13%	-0.146 (0.295)	-14%
Y2000	0.035 (0.660)	4%	0.005 (0.633)	0%	-0.017 (0.658)	-2%	-0.031 (0.645)	-3%
Y2001	0.093 (0.672)	10%	0.061 (0.643)	6%	0.033 (0.660)	3%	0.024 (0.653)	2%
Y2002	0.086 (0.657)	9%	0.035 (0.598)	4%	0.002 (0.603)	0%	-0.033 (0.597)	-3%
Y2003	0.220 (0.616)	25%	0.177 (0.586)	19%	0.160 (0.610)	17%	0.139 (0.598)	15%
Y2004	0.236 (0.603)	27%	0.199 (0.581)	22%	0.166 (0.606)	18%	0.168 (0.591)	18%
Y2005	0.289 (0.588)	33%	0.256 (0.563)	29%	0.224 (0.585)	25%	0.222 (0.571)	25%
Y2006	0.367 (0.584)	44%	0.342 (0.563)	41%	0.307 (0.584)	36%	0.307 (0.571)	36%
Fixed effects	Yes		Yes		Yes		Yes	
N	350		350		350		350	
Correctly classified	93.43%		93.66%		93.37%		93.08%	
Pseudo R-Squared	0.400		0.411		0.420		0.421	

Standard errors in parentheses. * Significant at 10%, ** Significant at 5%, *** Significant at 1%. Columns entitled "coeff" show the beta parameters of the MLE estimation. Columns entitled "OR" show the odd ratios of these estimation with $OR = (\exp(\beta) - 1) * 100$ in percentages.

We run a LR test to prove the correct specification of our model. The linear predicted value is a statistically significant predictor at the 1% level. The squared linear predicted value turns out to be insignificant. Both results verify the correct specification of our model. If the squared predictor were significant, the LR test would indicate misspecification of our model. The models classified more than 93% of all observations correctly. However, we must state that the MLE estimation dropped the 1998 and 1999 observations from the sample which leaves us with the sample size of $n=350$. Pearson's goodness-of-fit chi-squared tests are not statistically significant. We conclude that the model fits well (Cameron and Trivedi 2009). The Pseudo R-Squared that we reported at the end of the table is also considerably high. The estimations explain 40% and more of the information in the data.

The baseline shows that the general probability of RPS adoption has been mostly increasing over time. While the probability increases slightly up to 2002, there is a sudden increase in 2003. Afterwards, the baseline stabilizes again. Without drifting into speculations, one could argue that 2002 and 2003 were very special years for the U.S. energy landscape. In 2002, the 107th Congress debated the federal "Energy Policy Act of 2002" as a bundle of measures against the steady increase in oil prices. In 2003, the 107th Congress adopted the "Clear Skies Act of 2003". In the same year, the Northeastern blackout left 45 million U.S. Americans without electricity. California had just ended its energy crisis and the Enron scandal began to surface. These and other cross-state effects could have contributed to the sharp increase in the baseline probability in 2003.

A glance at the suite of controls provides two robust results. First, a Republican leaning public opinion decreases the chance of RPS adoption. Thus, policymakers are sensitive to their constituency's ideological stance. Second, states with large non-attainment areas are more likely to implement a RPS. Public health issues seem to drive the energy transition. Lyon and Yin (2010) also found a positive but insignificant link between the *NAA* Index and RPS adoption. We fail to reveal further control variables at the 10% significance level.

5.2. What Drives the Stringency of a RPS?

The tobit model concentrates on the state-years in which there is a RPS in place. The second research question asked for the determinants of policy stringency, which we quantify by means of the incremental share indicator (Yin and Powers 2010). The regression output in Table 4 shows that absolute contributions do not have a statistically significant impact on the dependent variable. However, as seen before in the hazard model, the relative contributions come at significant levels. We verify the hypothesis that REI contributions have a positive impact on the stringency of RPS schemes while CEI contributions appear to make them weaker. The effect is similar if the governor is a Democrat, while the significances disappear if a Republican is in office. In the fourth specification we interact the CEI and REI ratios with the *REG* index that represents the number of lobbying regulations. We find that CEI contributions keep their significant negative impact while REI contributions lose the significance.

What does that mean? We argue that high REI contributions motivate policymakers to implement a stronger RPS. As a result, more RES-E needs to be produced to meet the RPS requirement. More RES-E generation benefits the

constituency of REI interests. Vice versa, more CEI contributions motivate politicians to implement a weaker RPS. As a consequence, more conventional energy can remain in the portfolio. This is a benefit for the CEI. The overall effects seem to be driven by states with a Democratic governor and if there are only few lobby regulations in place. The absence of significant coefficients in the opposing scenarios (Republican governor, high *REG* index) does not indicate that these situations are not sensitive to contributions. The signs are still intuitive but the high p-values do not allow for a solid interpretation.

The suite of controls behaves similarly to the hazard model. A Republican leaning public opinion makes RPS policies, once implemented, less stringent. In contrast, public health costs, caused by people living in non-attainment areas, have a positive effect on the stringency of RPS policies. Both links verify our hypothesis while the remaining controls turn out to be insignificant. The baseline is different to the hazard baseline. While the hazard baseline sharply increased in 2003, the tobit baseline that captures the underlying trend in the stringency of RPS policies remains stable. One reason is that the majority of RPS policies have been enacted after 2003, the period that is mostly captured by the tobit model. Another reason can be that politicians react to cross-state impacts mainly by policy-making and less by policy redesigning.

Table 4 – Tobit Regression Results

	ISI			
	(T_I_1)	(T_I_2)	(T_I_3)	(T_I_4)
REI-A	0.155 (0.147)			
CEI-A	-0.064 (0.193)			
REI-R		0.228* (0.128)		
CEI-R		-0.016** (0.008)		
REI-R x GOV-D			0.189* (0.113)	
CEI-R x GOV-D			-0.011* (0.007)	
REI-R x GOV-R			-0.019 (0.079)	
CEI-R x GOV-R			-0.006 (0.004)	
REI-R x REG				0.217 (0.140)
CEI-R x REG				-0.017* (0.009)
GOV-R	-0.726 (0.517)	-0.755 (0.548)	-0.720 (0.556)	-0.743 (0.541)
PUB-R	-1.929* (1.005)	-1.982* (1.162)	-1.984* (1.160)	-1.936* (1.146)
N-RPS	-0.241 (0.821)	-0.301 (0.869)	-0.296 (0.867)	-0.292 (0.863)
INC	1.493 (1.900)	1.524 (1.938)	1.589 (1.946)	1.458 (1.918)
E-EMPL	0.109 (0.349)	0.089 (0.393)	0.085 (0.395)	0.092 (0.389)
NAA	0.584* (0.304)	0.631** (0.298)	0.615** (0.298)	0.634** (0.297)
Y1999	0.068 (0.059)	0.066 (0.087)	0.060 (0.085)	0.065 (0.087)
Y2000	0.128 (0.108)	0.125 (0.138)	0.120 (0.135)	0.124 (0.137)
Y2001	0.125	0.127	0.122	0.125

	(0.124)	(0.154)	(0.151)	(0.153)
Y2002	0.140	0.149	0.147	0.147
	(0.134)	(0.161)	(0.160)	(0.159)
Y2003	0.182	0.183	0.181	0.181
	(0.151)	(0.182)	(0.181)	(0.181)
Y2004	0.201	0.199	0.198	0.195
	(0.148)	(0.180)	(0.179)	(0.177)
Y2005	0.191	0.194	0.191	0.193
	(0.151)	(0.180)	(0.178)	(0.179)
Y2006	0.190	0.211	0.209	0.209
	(0.154)	(0.184)	(0.183)	(0.183)
Fixed Effects	Yes	Yes	Yes	Yes
N	129	129	129	129
Pseudo R-Squared	0.426	0.387	0.403	0.397

Standard errors in parentheses. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.

The sample size of the tobit model is rather small. Future studies will certainly make more accurate estimations because they can work with an increasing number of state-years that have a RPS in place. However, our estimates are robust across model specification. The Pseudo R-Squared is lower than in the hazard model but still considerably high.

6. Conclusion

This article combined theoretical reasoning and empirical analysis. We applied the common agency model developed by Dixit et al. (1997) to the puzzle of renewable energy policy making. Henceforward we elaborated model specifications that explained how the decisions of policymakers (i) to enact a RPS and (ii) to set the stringency of the RPS after enactment are driven by both social welfare considerations and financial contributions from private industrial interests.

We went on to quantify the financial contributions by conventional energy interests (CEI) and renewable energy interests (REI) that were donated to U.S. state-level policymakers between 1998 and 2010. We found that CEI contribute more to Republicans than to Democrats while REI contributions are mostly given to Democrats.

By means of a proportional hazard model, we revealed statistically significant links between the contributions and the likelihood of a state to adopt a RPS. In short, CEI contributions have a negative impact on the probability of RPS adoption while REI contributions have a positive impact. We conclude that policymakers are sensitive to private interest contributions. REI contributions signal support for a RPS while CEI contributions indicate opposition. We assume that policymakers know that REI benefit from a RPS while CEI prefer its absence. Thus, the hazard model showed that this presumable connection stands up to empirical scrutiny. Public health issues, proxied by the EPA's non-attainment area index, also drive the likelihood of RPS adoption. On the other hand, the odds are also affected by public opinion. The impact of our control for a Republican leaning public option turned out to be negative.

By means of a tobit regression model, we revealed similar but less significant links. After a RPS is implemented, REI contributions appear to have a positive impact on the stringency of the policy. In contrast, CEI contributions come with a negative impact. The same controls, public health and public opinion, remain robust for all model specifications.

From a theoretical perspective the results verify our key hypothesis. They prove that policymakers set the optimal level of RES-E not only by maximizing benefits over

social welfare but they also integrate financial contributions from private industrial interests. From an empirical perspective the results show that policymakers pay back the financial contributions by means of policy choices and – albeit limited – also by policy stringency. Future studies should not rely on binary codes to assess the impact of private interests anymore but should use more nuanced indicators such as our financial contributions.

7. References

- Aidt, T. S., 1998. Political internalization of economic externalities and environmental policy. *Journal of Public Economics* 69(1), 1 - 16.
- Cameron, A.C., Trivedi, K.T., 2009. Microeconomics using Stata. Bloomington, Indiana: Stata Press.
- Chandler, J., 2009. Trendy solutions. Why do states adopt Sustainable Energy Portfolio Standards? *Energy Policy* 37(8), 3274 - 3281.
- Davidson, R., MacKinnon, J.G., 1993. Estimation and Inference in Econometrics, New York, Oxford University Press.
- Database of State Incentives for Renewable Energy (DSIRE), 2012. Database of State Incentives for Renewables and Efficiency. January. Accessed at <http://www.dsireusa.org/>.
- Delmas, M. A., Montes-Sancho, M. J., 2011. U.S. state policies for renewable energy: Context and effectiveness. *Energy Policy* 39(5), 2273 - 2288.
- Dixit, A., 1996. Special-interest lobbying and endogenous commodity taxation. *Eastern Economic Journal* 22, 375 – 388.
- Dixit, A., Grossman, G.M., Helpman, E., 1997. Common agency and coordination: General theory and application to government policy making. *Journal of Political Economy* 105(4), 752 - 769.
- Finon, D., Menanteau, P., 2004. The static and dynamic efficiency of instruments of promotion of renewables. *Energy Studies Review* 12(1), 53 – 82.
- Fischer, C., Newell, R.G., 2008. Environmental and technology policies for climate mitigation. *Journal of Environmental Economics and Management* 55(2), 142 - 162.
- Groba, F., Indvik, J., Jenner, S., 2011. Assessing the Strength and Effectiveness of Renewable Electricity Feed-in-Tariffs in European Union Countries. Discussion Paper # 1176, DIW Berlin, Berlin.
- Grossman, G.M., Helpman, E., 1994. Protection for sale. *American Economic Review* 84, 833 – 850.
- Huang, M.-Y., Alavalapati, J.R., Carter, D.R., Langholtz, M.H., 2007. Is the choice of renewable portfolio standards random? *Energy Policy* 35(11), 5571 – 5575.
- Jenkins, P., 1995. Easy Estimation Methods for Discrete-Time Duration Models. *Oxford Bulletin of Economics and Statistics* 57(1), 129 - 138.
- Jenner, S., Chan, G., Frankenberger, R., Gabel, M., 2012. What Drives States to Support Renewable Energy? *The Energy Journal* 33(2), 1 - 12.
- Kiefer, N.M., 1988. Economic duration data and hazard functions. *Journal of Economic Literature* 26(2), 646 – 679.
- Knittel, C.R., 2006. The adoption of state electricity regulation. The role of interest groups. *Journal of Industrial Economics* 54(2), 201 – 222.
- League of Conservation Voters, 2011. Environmental Scorecard, 1998–2010 scorecards. October. Accessed at <http://www.lcv.org/scorecard/scorecard-archives/>.

- Lyon, T.P., Yin, H., 2010. Why do states adopt renewable portfolio standards? An empirical investigation. *The Energy Journal* 31(3), 133 – 157.
- Menanteau, P., Finon, D., Lamy, M., 2003. Prices versus quantities: Choosing policies for promoting the development of renewable energy. *Energy Policy* 31(8), 799 - 812.
- National Institute on Money in State Politics, 2011. State contributions. All state campaign contribution records. November. Accessed at <http://data.influenceexplorer.com/bulk/>.
- Nese, G., 2002. Green certificates in an international market. Institute for Research in Economics and Business Administration (SNF) University of Bergen, SNF Working paper 75/02, Bergen.
- Newmark, A.J., 2005. Measuring State Legislative Lobbying Regulation, 1990-2003. *State Politics & Policy Quarterly* 5(2), 182 – 191.
- Persson, T., Tabellini, G., 2000. Political Economics: Explaining Economic Policy. Cambridge and London: MIT Press.
- Schmalensee, R., 2011. Evaluating Policies to Increase the Generation of Electricity from Renewable Energy. M.I.T. Center for Energy and Environmental Policy Research Working Paper 2011-008, Cambridge, M.A.
- U.S. Bureau of Labor Statistics, 2011. Databases. Employment. October. Accessed at <http://www.bls.gov/data/#employment>.
- U.S. Bureau of Economic Analysis, 2011. Regional Economic Accounts. State Annual Personal Income & Employment. December. Accessed at <http://www.bea.gov/regional/index.htm>.
- U.S. Energy Information Administration, 2011. The Electric Power Annual Database. U.S. Energy Information Administration, Washington, D.C.
- U.S. Environmental Protection Agency, 2011. The Green Book Nonattainment Areas for Criteria Pollutants. December. Accessed at <http://www.epa.gov/oar/oaqps/greenbk/>.
- U.S. National Conference of State Legislatures, 2011. Legislator Data (private).
- Weitzman, M.L., 1974. Prices vs. quantities. *The Review of Economic Studies* 41(4), 477 - 491.
- Wooldridge, J., 2002. Econometric Analysis of Cross Section and Panel Data. MIT Press, Cambridge, MA.
- Yin, H., Powers, N., 2010. Do state renewable portfolio standards promote in-state renewable generation? *Energy Policy* 38(2), 1140 – 1149.

8. Appendices

8.1. Theory

The FOC of the benchmark case (no lobbying) implicitly defines the optimal level α^* :

$$\frac{\partial SW}{\partial \alpha} = 0 = \pi_{\alpha}^R - NH_{\alpha}(E) - NPx_{\alpha}(P) + \pi_{\alpha}^F + \pi_{\alpha}^D + N[u(x_{\alpha}(P))] \quad (14)$$

The first three terms are positive: the profits for the renewables producers increase, pollution decreases and utility of consuming the numéraire increases with an increase in α . The other terms in the expression are negative. The profits in the fossil fuel and distribution sector decrease as well as the demand for electricity, so that utility of consuming electricity is lower, when the RPS obligation strengthens. The optimal level of renewables under the RPS, α^* , is defined by equating these marginal benefits and marginal costs. The objective function of the policymaker that includes campaign contributions from the renewables interest group has the following FOC:

$$\begin{aligned} \frac{\partial SW}{\partial \alpha} = 0 = & \lambda \left[\pi_{\alpha}^R - NH_{\alpha}(E) - NPD_{\alpha}(P) + \pi_{\alpha}^F + \pi_{\alpha}^D + N[u(D_{\alpha}(P))] \right] \\ & + (1 - \lambda) \left[\sum_{h \in REI} \sigma_{h,R} \pi_{\alpha}^R - s_R NH_{\alpha}(E) \right] \end{aligned} \quad (15)$$

This condition implicitly defines the optimal level of the portfolio standard in presence of influence from the renewables interests. Marginal benefits of increasing the level of the standard are larger compared to the benchmark case, which allows us to conclude that the optimal level of the standard is larger than α^* , we have $\alpha^R > \alpha^*$. The FOC for the objective function where the policymaker includes campaign contribution from the conventional interests is as follows:

$$\begin{aligned} \frac{\partial SW}{\partial \alpha} = 0 = & \lambda \left[\pi_{\alpha}^R - NH_{\alpha}(E) - NPD_{\alpha}(P) + \pi_{\alpha}^F + \pi_{\alpha}^D + N[u(D_{\alpha}(P))] \right] \\ & + (1 - \lambda) \left[\sum_{h \in CEI} \sigma_{h,F} \pi_{\alpha}^F \right] \end{aligned} \quad (16)$$

This expression implicitly defines α^F , the optimal standard in presence of the conventional interest group. As the marginal costs of increasing the standard exceed the marginal benefits, the policymaker maximizes his objective function by imposing a level that is lower than in the benchmark, so we have $\alpha^F < \alpha^*$.

8.2. Additional Regressions

Table 5 presents the results of our simple time series cross-sectional regression model. It does not reveal significant connections between CEI or REI contributions and the dependent variables *RPS Binary* or *ISI*.

Table 5 – Times Series Cross-Sectional Regression Results

	RPS Binary				ISI			
	(X_B_1)	(X_B_2)	(X_B_3)	(X_B_4)	(X_I_1)	(X_I_2)	(X_I_3)	(X_I_4)
REI-A	0.005 (0.005)				0.089 (0.093)			
CEI-A	-0.001 (0.011)				-0.030 (0.219)			
REI-R		-0.003 (0.002)				-0.004 (0.025)		
CEI-R		-0.000 (0.001)				-0.002 (0.009)		
REI-R x GOV-D			-0.001 (0.003)				0.042 (0.066)	
CEI-R x GOV-D			-0.000 (0.000)				-0.003 (0.007)	
REI-R x GOV-R			-0.004** (0.002)				-0.004 (0.037)	
CEI-R x GOV-R			-0.000 (0.000)				0.000 (0.004)	
REI-R x REG				-0.002 (0.002)				-0.002 (0.018)
CEI-R x REG				-0.000 (0.001)				-0.002 (0.009)
GOV-R	-0.005 (0.015)	-0.006 (0.016)	-0.003 (0.017)	-0.007 (0.016)	0.304 (0.285)	0.298 (0.310)	0.314 (0.318)	0.286 (0.312)
PUB-R	-0.073 (0.067)	-0.092 (0.082)	-0.092 (0.082)	-0.095 (0.083)	0.298 (0.967)	0.067 (1.187)	0.106 (1.171)	0.010 (1.202)
N-RPS	0.037 (0.036)	0.033 (0.037)	0.034 (0.037)	0.032 (0.037)	0.937 (0.742)	0.999 (0.800)	1.004 (0.803)	0.981 (0.800)
INC	0.107 (0.153)	0.096 (0.153)	0.100 (0.156)	0.089 (0.151)	1.431 (3.489)	1.888 (3.457)	1.959 (3.458)	1.749 (3.437)
E-EMPL	-0.016 (0.015)	-0.016 (0.016)	-0.016 (0.016)	-0.016 (0.016)	0.075 (0.381)	0.062 (0.427)	0.068 (0.423)	0.057 (0.432)
NAA	0.018 (0.012)	0.020* (0.012)	0.019 (0.012)	0.021* (0.012)	0.186 (0.289)	0.158 (0.279)	0.156 (0.280)	0.170 (0.277)
RES-CAP	-0.007 (0.010)	-0.006 (0.010)	-0.006 (0.010)	-0.006 (0.010)				
constant	-0.003 (0.015)	-0.002 (0.015)	-0.002 (0.015)	-0.001 (0.015)	-0.221 (0.341)	-0.266 (0.342)	-0.276 (0.339)	-0.250 (0.342)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	450	450	450	450	450	450	450	450
R-Squared	0.1683	0.1696	0.1713	0.1717	0.4085	0.3931	0.3937	0.3954

Standard errors in parentheses. * Significant at 10%, ** Significant at 5%, *** Significant at 1%.