Do RTOs Promote Renewables?

A Study of State-Level Data over Time

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Abstract

We examine data for the 48 contiguous states from calendar years 1990 to 2005 to explore whether a state's membership in an organized wholesale market promotes the development of renewable electricity generation. Since states in regional transmission organizations (RTOs) generate most of the renewable electricity, some have asserted this is a benefit of RTOs. We find that, in contrast to wind, much of the development of geothermal, wood, and waste biomass took place prior to states joining RTOs. The development of solar and geothermal is concentrated in only a few states, preventing a firm conclusion about the role of RTOs. Our statistical analysis of wind, wood, and waste estimated a structural model of renewables development using feasible generalized least squares to correct for autocorrelation and heteroscedasticity. The estimated coefficients have the hypothesized signs except for the negative, statistically significant coefficient for membership in an RTO, implying that membership in an RTO impedes the development of the wind resource. The regressions for wood and waste biomass do not show a significant coefficient with RTO membership. We explored a wide range of plausible specifications for the relationship between renewables, membership in an RTO, and other factors, finding little indication that RTOs promote renewables. We cannot explain the indication that RTOs are negatively correlated with the development of wind.

1 Introduction

Do organized wholesale markets promote renewable energy? In a recent open letter to the Federal Energy Regulatory Commission (FERC) and members of congress, representatives from 22 organizations devoted to renewables have asserted that they do [1].

Fueling the speculation that renewable promotion is an unexpected benefit of joining a regional transmission organization (RTO) or independent system operator (ISO) is the current breakdown of where wind assets are located. We estimate that 66% of United States wind generated electricity was produced in RTO states in 2005, even though those states represent only 30% of US wind resource potential and 48% of national electric generation from all sources[1] [3, 4].

While RTOs may promote renewables, their concentration in RTO states could also be caused by higher electric prices or other factors; investments in renewables may even have occurred prior to states joining RTOs. Several groups have argued that RTOs promote wind by compensating for wind variability over a large number of traditional generators and via a transparent market signal to independent power producers (IPPs) [1, 2, 5]. They also state that transmission planning processes in RTOs have helped integrate remote renewables. These arguments apply to wind; the non-dispatchability point also applies to solar; the remoteness argument also applies to geothermal. Only the market transparency point applies to biomass generation.

We do not evaluate these qualitative arguments in detail, but rather we investigate production data to find whether renewables production actually *has* increased more in RTO states over 1990-2005. Our hypothesis is that a statistical analysis will find a positive association between RTO status and renewable production after controlling for other possible structural variables.

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[1] The ISO-RTO Council has claimed that for the US and Canada combined 79% of wind capacity is in RTO territory with only 44% of wind resources and 53% of electric demand [2].

2 Data

Table 1 summarizes the data for 1990-2005 for all 48 contiguous states[2]. These data are available from the authors upon request. The variables *WindPot, BioRes1*-*BioRes5,* and *Dem* are constant over time for each state; the other variables change with time.

Table 1. Study data.

	Variable	Data	Units	Sources
Generation	*MWh*	Total state electric generation	MWh	[3, 6]
	Wind	Wind generation	MWh	
	Solar	Solar generation[3]	MWh	
	Geo	Geothermal generation	MWh	
	Wood	Wood biomass fuel consumption for electricity	BTU	
	Waste	Waste biomass fuel consumption for electricity	BTU	
RTO Status	*RTOFull*	Years a state has been fully in an RTO	years	[7-13]
	RTOPart	Years a state has been partly in an RTO	years	
	RTO	Years a state has been either partly or fully in an RTO	years	
State	*Price*	State electric price in real dollars	2000$/kWh	[14-19]
	Policy1 – Policy8	Eight variables indicating state policies on renewables	--	
	GSP	Real gross state product per capita[4]	2000$	
	Dem	Percent democratic vote 2004 presidential[5]	--	
Time	*Y*1990-*Y*2005	Dummy variable for each year 1990 to 2005	--	--
Resource[6]	*WindPot*	Wind resource potential in the state	MWh	[4, 22]
	BioRes1 – BioRes5	Five variables indicating biomass resource potential	--	

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[2] Alaska and Hawaii are excluded for several reasons. First, many of the specified data such as resource potential are not available from these sources. Second, both Alaska and Hawaii can be seen as special cases because of their differences in geography, climate, and distance when compared with the contiguous 48 states.

[3] The database also contains estimates of residential and commercial solar BTU "consumption" for the combination of solar thermal and photovoltaic (PV) units, but the numbers are not disaggregated [3]. The estimate is entirely based on shipments of solar thermal collectors by state and does not account for PV shipments. We do not include these numbers in our solar generation variable.

[4] The real gross state product is normalized by the state population according to the 1990 census [18].

[5] Percent of major party votes after excluding the count of third party votes.

[6] We also collected data for the renewable resource potentials of solar and geothermal resources and will make those data available upon request [20, 21]. We do not report them here however because as discussed in Section 3.2 and 3.3, there is not enough output of these types of renewables to perform meaningful regressions with the data.

We make the following additional notes on data collection.

RTO Status

We use three different classification schemes to account for RTO status. In the first, we track the number of years that a state territory has been at least partly (and perhaps entirely) within an RTO with variable *RTO*. In the second, we distinguish between the number of years that a state has spent partly within RTO territory *RTOPart* and fully within RTO territory *RTOFull*. In the third we use dummy variables (1 or 0) to account for RTO membership.

The classification of states as fully, partly, or not at all within RTOs required judgment in some cases. For example, we treat California as fully within an RTO even though there are actually some sections of California not within California ISO (CAISO) territory. Figure 2 shows our classification of each state over time. We treat the date that wholesale market operations began as the start date for RTO classification and count the fraction of the year that the state has been within the RTO.

State Renewables Policies

The status and enacted dates of these 19 state policies[7] are from the *Database of State Incentives for Renewables and Efficiency* (DSIRE), as shown in Figure 1 [17]. We track the number of years that each policy has been in effect for each state. Since these 19 variables were correlated, we calculated their principal components. We use the top eight components, see Appendix A.1

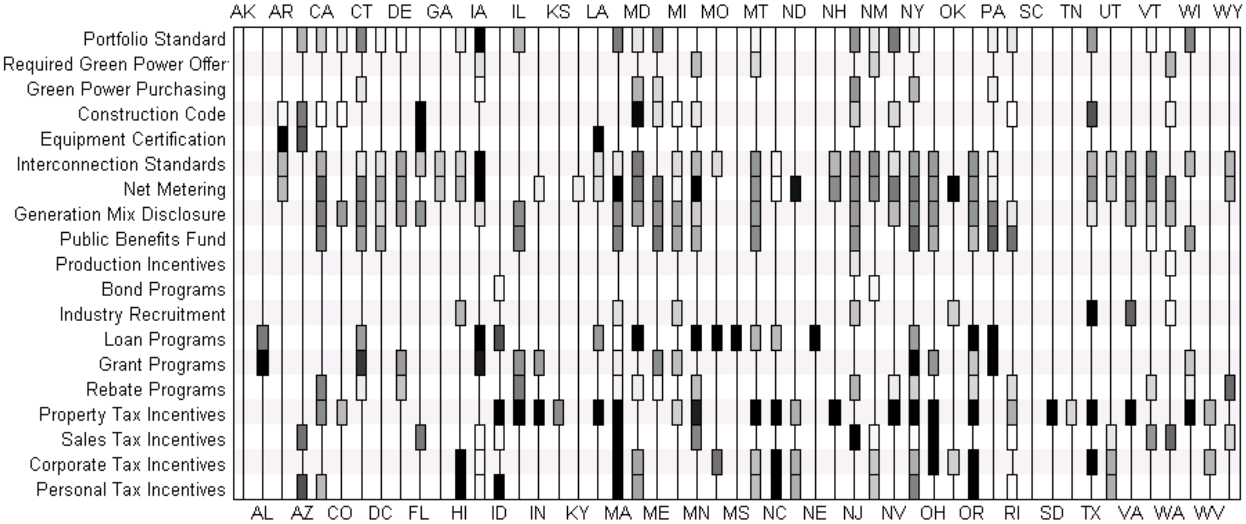

Figure 1. State policies on renewable energy by state [17]. The darker the box, the longer the policy had been in place as of 2005. A totally black box indicates that the policy had been in place at least since 1990; a totally white box indicates that the policy was enacted exactly at the end of 2005.

Time

The dummy variables for year implicitly control for factors that are constant across all states in a given year, e.g., the presence or absence of the federal production tax credit (PTC) [23].

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[7] The database also contained information on access laws, contractor licensing, and line extension analysis policies but these are not accounted for here because of difficulty in determining the dates when these policies were enacted in each state.

Biomass Resource Potential

The 28 biomass resource variables indicate total available dry tons of six types of biomass including urban waste, mill waste, forest residue, agricultural residue, switchgrass, and short rotation woody crops. The data indicate the quantity of each biomass fuel available at or below prices of $20, $30, $40, or $50 per dry ton [22]. The data are appropriate indicators of both wood and waste biomass resources. We controlled for the correlation among the 28 using principal components, using the top five components, see Appendix A.2.

3 Timing of RTO Formation and Locational Growth in Renewables

The most basic way to evaluate whether RTO status impacts renewables is to ask whether investments were made before RTO entry. Figure 2 shows RTO entry dates from 1995-2006.

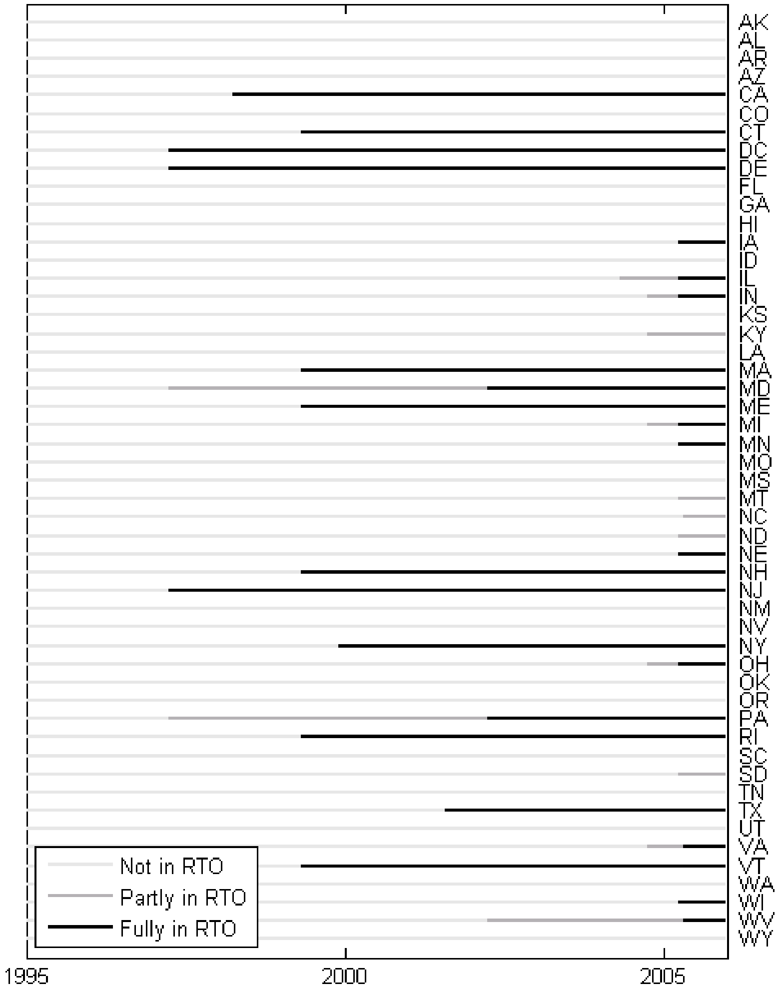

Figure 2. Timeline of RTO entry by state, Jan 1995-Dec 2005 [7-12].

Figure 3 shows the growth in renewable power over the last half century. Data before 1988 cover utilities only; beginning in 1989 these EIA data also cover independent power producers, leading to a discontinuity in the figure. There are several interesting features in these data. The first is that growth in wind took off starting in 1998. This roughly coincides with the advent of organized markets; PJM was the first market to begin wholesale operations in April, 1997 [13].

Three factors aside from RTO formation promoted wind at that time. First, many states adopted renewable portfolio standards (RPSs) in the late 1990s and early 2000s [17]. Second, federal PTCs that promoted wind production lapsed three times between 1998 and 2005. Samaras has shown that new wind capacity came online in big jumps just before these lapses in order to lock in the 10-year PTC guarantee [23]. Third, technology improved significantly in the 1980s and 1990s, driving costs below a critical threshold that made wind profitable in some places; capital costs decreased from almost $2,500/kW in 1990 to just above $1,500/kW in 1998 [24]. Finally, this figure does not compare growth rates between RTO and non-RTO states, see Section 3.1.

Figure 3 shows that solar was only 0.5% of the total non-hydroelectric renewables mix in 2006. Geothermal generation is substantial, but has not grown since the advent of RTOs. Between 2000 and 2001, biomass waste dropped sharply and then rebounded slowly; biomass wood began growing slowly at the same time.

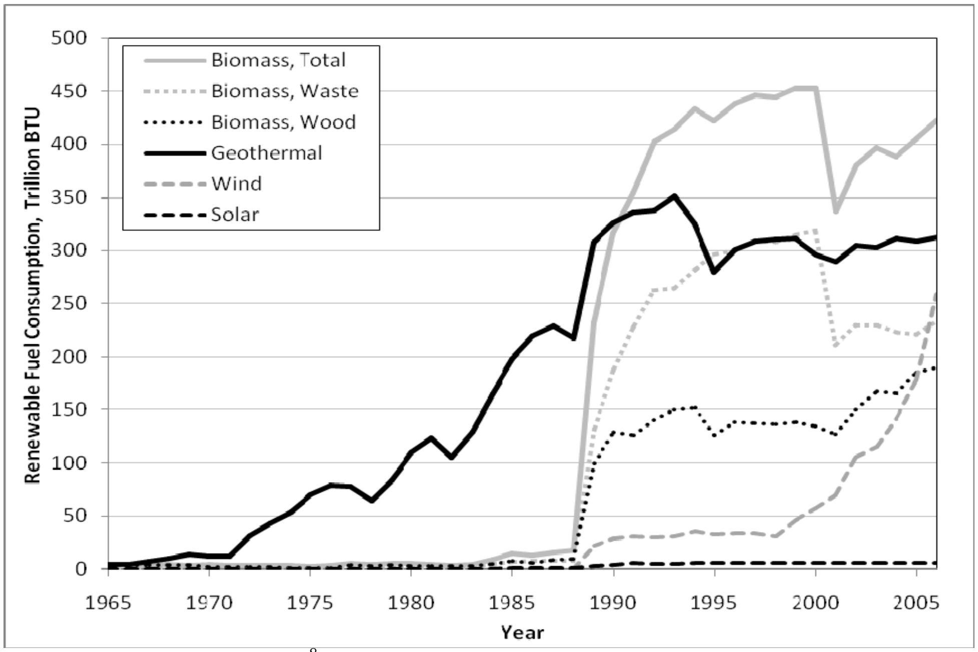

Figure 3. Fuel consumption[8] for renewable power generation [25].

3.1 Wind Generation over Time

Figure 4 shows wind production over time within each RTO. We do not show Midwest ISO or Southwest Power Pool data because of their recent market start dates[9]. PJM has expanded several times and has many states only partly within its territory; we therefore show only states that were in PJM territory when it introduced the wholesale market on April 1, 1997. The last plot in the figure shows the growth of wind in states that had not joined an RTO by 2005.

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[8] Solar and wind were converted to BTU using typical heat rates from fossil plants.

[9] Midwest ISO began market operations on April 1, 2005; the Southwest Power Pool began February 1, 2007 respectively.

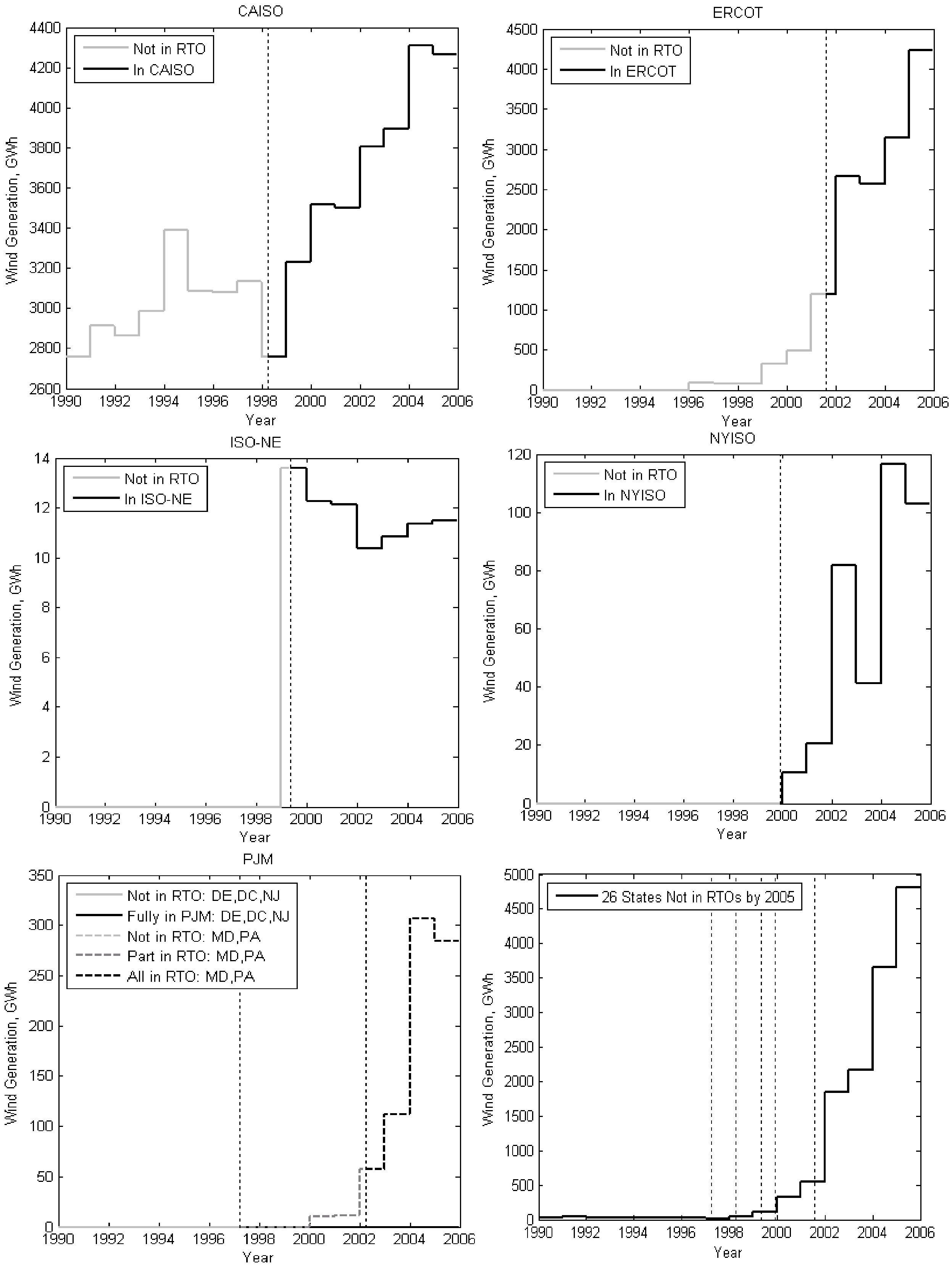

Figure 4. Wind generation timeline for each RTO, vertical lines show market start dates. The last plot shows wind growth in non-RTO states.

The left-hand plot of Figure 5 shows the growth of wind from 1990-2006 separating those 14 states[10] that were fully within RTOs by the middle of 2002 from the 26 states[11] that had not joined RTOs by the end of 2005. The remaining 11 states[12] had either partly or fully joined RTOs by the end of 2005. The right-hand plot of Figure 5 shows the same data after California has been removed. Vertical dashed lines indicate the start dates of the five RTOs from Figure 4; PJM's expansion in 2002 is not shown.

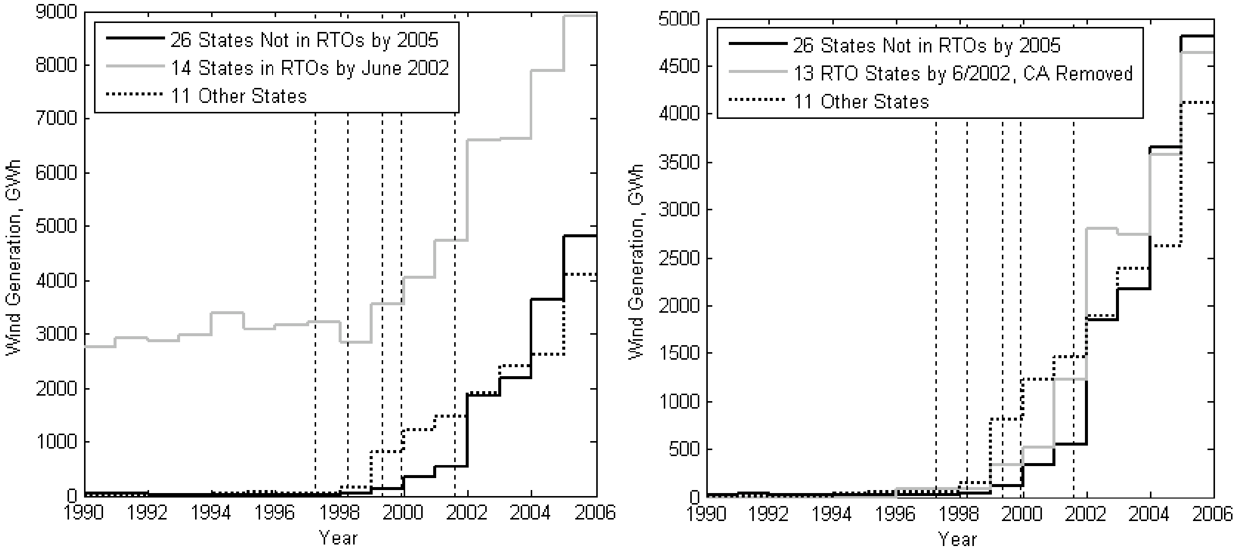

Figure 5. Comparison of wind in RTO and non-RTO states, including DC.

The plots in Figure 4 show that in each of the five RTOs examined, the takeoff of the growth in wind roughly, but only roughly, coincided with the introduction of the organized wholesale market. The suggestion is weakened however after looking at the growth of wind in non-RTO states in the last plot of Figure 4. Growth in wind took off in *both* RTO states *and* in non-RTO states at the same time. We proceed to a formal statistical analysis of these data.

Wind generation is concentrated in a few states. Figure 6 and Table 2 show the fraction of total US wind generation from the top producers. Since California and Texas account for almost half the wind energy and Iowa and Minnesota adding 18% more, these four states will dominate the analysis, see Section 4.1.

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[10] This actually refers to 13 states and the District of Columbia: CA, CT, DC, DE, MA, MD, ME, NH, NJ, NY, PA, RI, TX, and VT.

[11] The 26 states are: AK, AL, AR, AZ, CO, FL, GA, HI, ID, KS, LA, MO, MS, NM, NV, OK, OR, SC, TN, UT, WA, and WY.

[12] The 11 other states are: IA, IL, IN, KY, MI, MN, MT, NC, ND, NE, OH, SD, VA, WI, and WV.

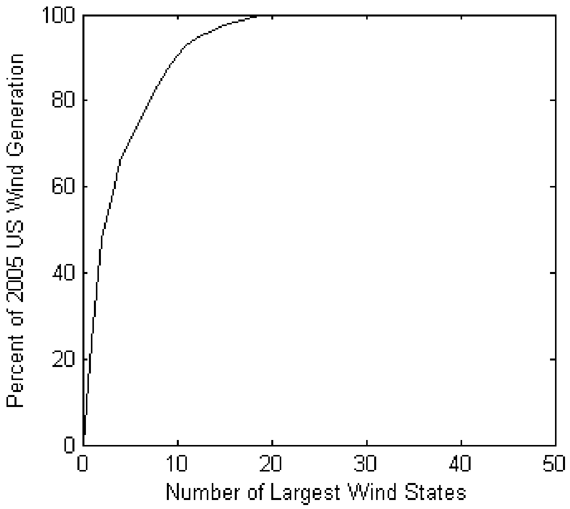

Figure 6. Concentration of wind generation.

Table 2. Concentration of wind generation in top producing states.

	Wind Generation % in 2005		Date of RTO Entry
	Cumulative of Top Wind Producers	Individual State	
CA	23.9%	23.9%	4/1/1998
TX	47.7%	23.8%	8/1/2001
IA	57.0%	9.2%	4/1/2005
MN	65.9%	8.9%	4/1/2005
OK	70.6%	4.8%	2/1/2007
NM	75.1%	4.5%	2/1/2007
CO	79.4%	4.4%	Not in RTO
OR	83.6%	4.1%	Not in RTO
WY	87.6%	4.0%	Not in RTO
WA	90.4%	2.8%	Not in RTO
KS	92.8%	2.4%	2/1/2007

3.2 Solar Generation Over Time

Figure 7 shows the growth of solar between 1990 and 2005. Arizona, California, Texas, and Virginia are the only states with any history of solar production the power sector[13]. In 2005 only two states produced any solar; California produced 97.5% and Arizona produced the remaining 2.5%.

California solar output was growing steadily over the whole period; Texas solar output hit zero before commencement of ERCOT market operations. Arizona, a non-RTO state had a dramatic jump in solar production in both 2004 and 2005.

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[13] As discussed in Section 2, these data do not track commercial or residential solar electric production.

Virginia, the only solar producer not shown in Figure 7, partly entered PJM in October 2004, and fully entered PJM in May 2005. Virginia is a very small solar producer, with a maximum annual output of 0.034 GWh in 1990 and zero output since 1996.

The plots in Figure 7 and the data from Virginia show no indication that RTO status has influenced the production of solar energy.

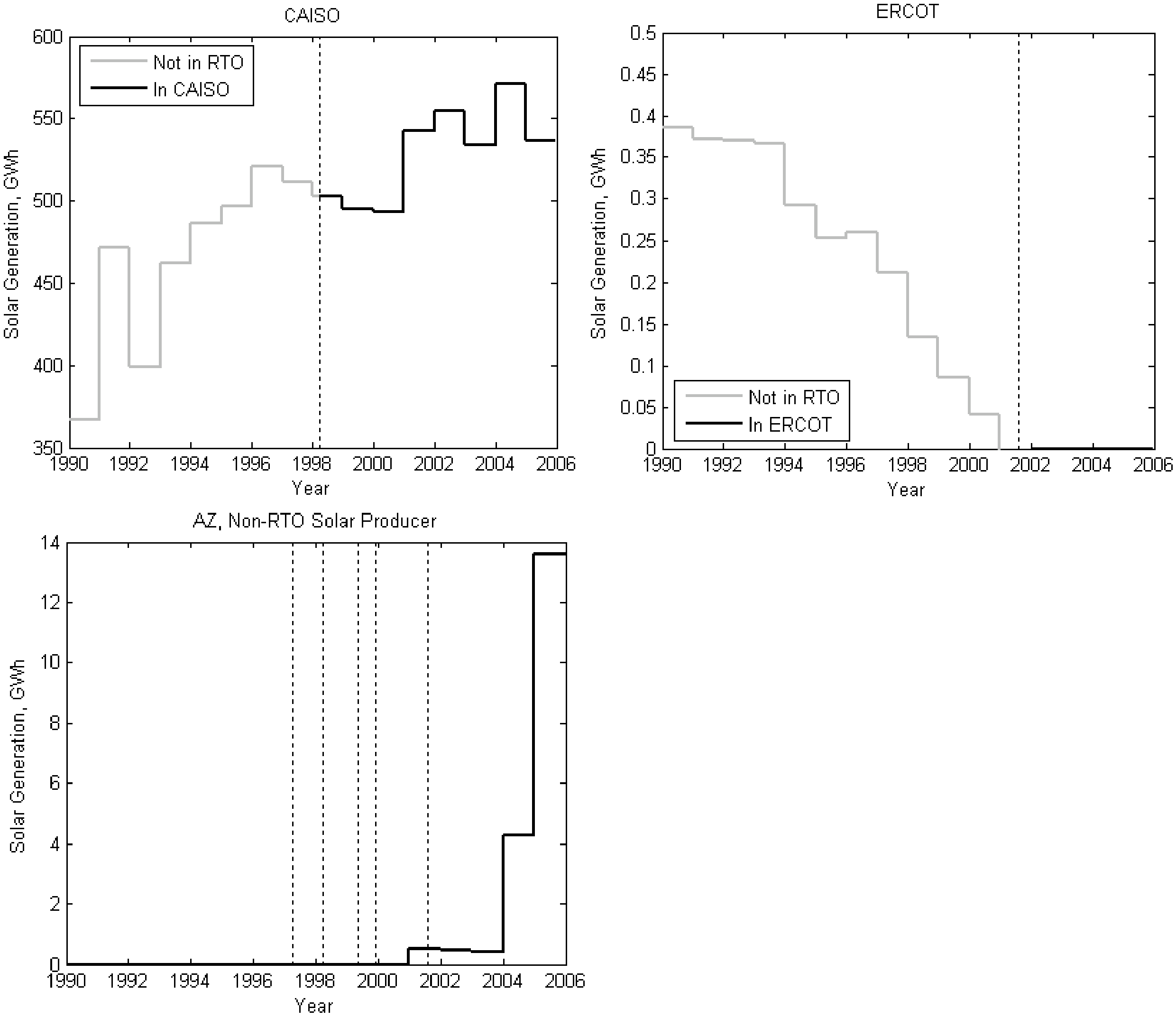

Figure 7. Solar generation timeline for CAISO and ERCOT, the only two RTOs with solar production between 1990 and 2005. The last plot shows output from AZ, the only non-RTO solar producer.

These data do not indicate a relationship between RTO membership and solar generation.

3.3 Geothermal Generation Over Time

Figure 8 shows the growth of geothermal over time. Only four states have any history of geothermal generation. California is the only RTO state with any history of Geothermal Generation; its geothermal output was large well before market operations began in April 1998. The remaining three geothermal producers, Hawaii, Nevada, and Utah, are shown on the right have never been in an RTO.

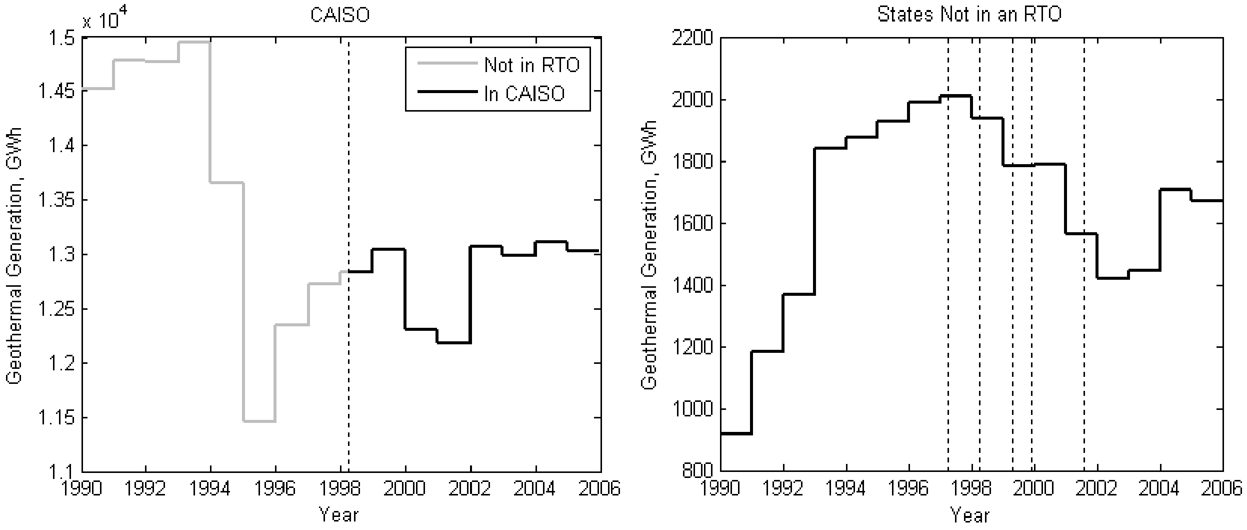

Figure 8. Geothermal generation timeline for CAISO with market start date. The right-hand plot shows output from non-RTO states.

Table 3 shows what fraction of that generation comes from each of the four producing states.

Table 3. Concentration of geothermal generation in all four producing states.

	Geothermal Generation % in 2005		Date of RTO Entry
	Cumulative of Top Producers	Individual State	
CA	88.6%	88.6%	4/1/1998
NV	97.2%	8.59%	Not in RTO
HI	98.7%	1.51%	Not in RTO
UT	100%	1.26%	Not in RTO

We find no evidence that membership in an RTO promotes geothermal generation.

3.4 Wood Biomass Generation Over Time

Figure 9 shows the growth of wood biomass consumption for electric generation in each RTO. Although the volatility makes it hard to observe a trend, wood biomass may have increased in CAISO, ISO-NE, and PJM when markets began operations; over the same time period of 1997-2002, wood biomass in non-RTO states dropped fairly sharply. These data point to the need for a statistical analysis.

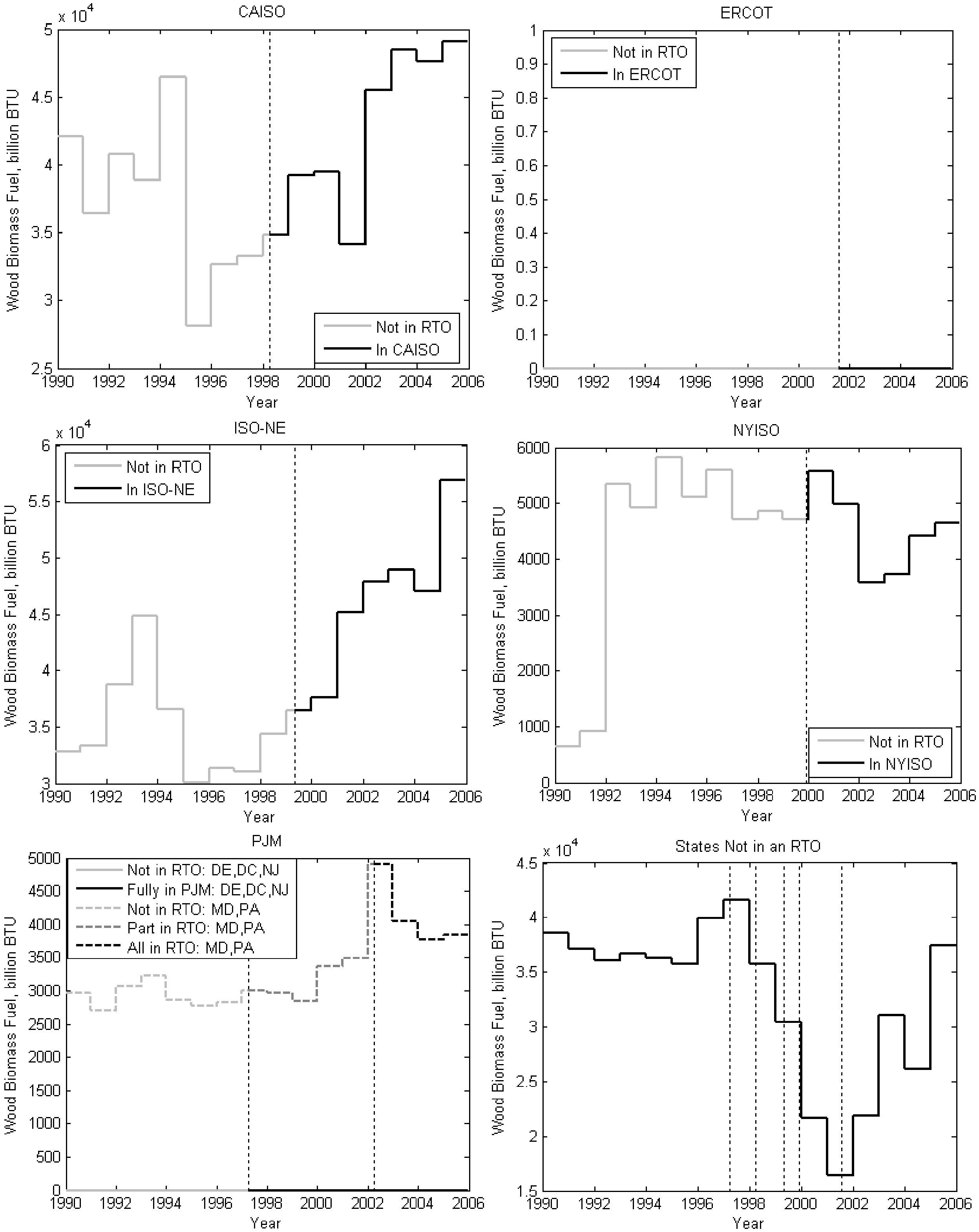

Figure 9. Wood biomass consumption for electric generation in each RTO with market start dates. The last plot shows consumption from all states that were not in RTOs by the end of 2005.

The left-hand plot of Figure 10 shows the growth of wood biomass from 1990-2006 separating those 14 states[14] that were fully within RTOs by the middle of 2002 from the 26 states[15] that had not joined RTOs by the end of 2005. The remaining 11 states[16] had either partly or fully joined RTOs by the end of 2005. The right-hand plot of Figure 10 shows the same data after California has been removed. Vertical dashed lines show the start dates of the five RTOs from Figure 9 and Figure 4; PJM's expansion in 2002 is not shown.

Again we observe a drop in wood biomass consumption in non-RTO states as it is increasing in RTO states between 1997 and 2002, suggesting the need for a statistical analysis.

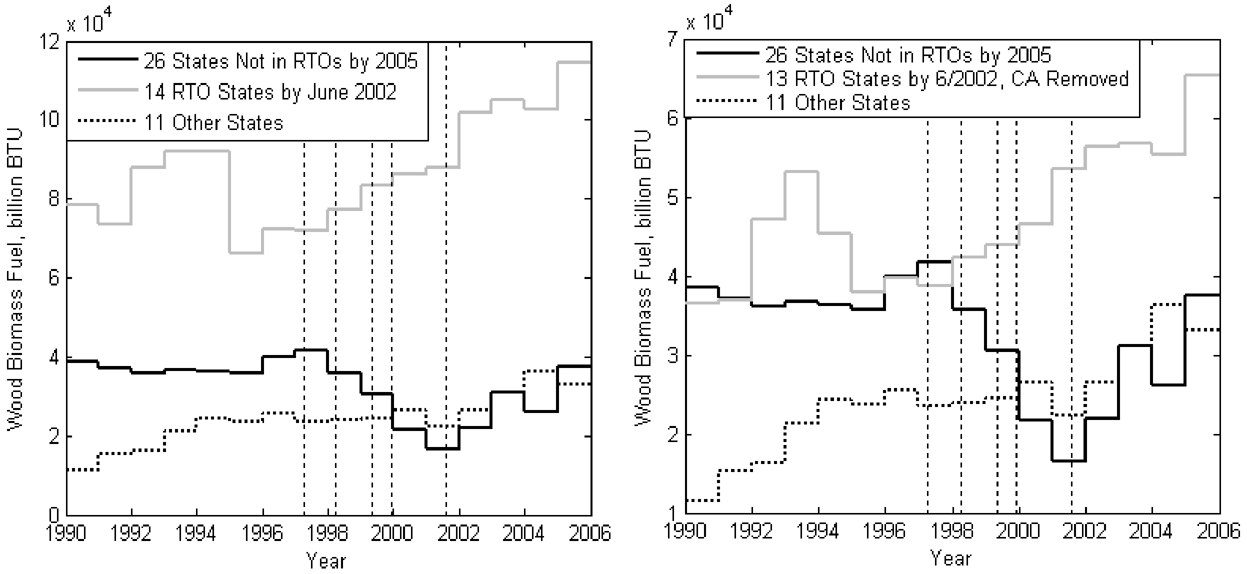

Figure 10. Comparison of wood biomass in RTO and non-RTO states, including DC.

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[14] This actually refers to 13 states and the District of Columbia: CA, CT, DC, DE, MA, MD, ME, NH, NJ, NY, PA, RI, TX, and VT.

[15] The 26 states are: AK, AL, AR, AZ, CO, FL, GA, HI, ID, KS, LA, MO, MS, NM, NV, OK, OR, SC, TN, UT, WA, and WY.

[16] The 11 other states are: IA, IL, IN, KY, MI, MN, MT, NC, ND, NE, OH, SD, VA, WI, and WV.

Table 4 shows the fraction of wood biomass consumption for electric generation occurs in the top wood biomass states. As in the cases of other renewables, we see that almost half of the consumption is in two states.

Table 4. Concentration of biomass wood consumption for electric generation in top producing states.

	Wood Biomass % in 2005		Date of RTO Entry
	Cumulative of Top Consumers	Individual State	
CA	26.6%	26.6%	4/1/1998
ME	48.0%	21.5%	5/1/1999
MI	56.5%	8.46%	10/1/2004[17]
FL	62.4%	5.93%	Not in RTO
NH	67.7%	5.33%	5/1/1999
WA	72.4%	4.62%	Not in RTO
VA	75.9%	3.57%	10/1/2004[18]
SC	79.4%	3.48%	Not in RTO
OR	82.8%	3.41%	Not in RTO
NC	85.8%	2.96%	5/1/2005[19]
VT	88.6%	2.86%	5/1/1999
NY	91.2%	2.51%	12/1/1999
PA	93.2%	2.07%	4/1/1997[20]
AL	95.1%	1.82%	Not in RTO

3.5 Waste Biomass Generation Over Time

Figure 11 shows the growth of waste biomass consumption for electric power production over time within each RTO formed before 2002. The last plot also shows consumption in the states that were not in RTOs by the end of 2005. Any trends that may be related to RTO formation are not clear given the volatility, but none of the RTOs appears to have had growth in waste biomass that is different from the slow growth in non-RTO states.

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[17] Partly entered PJM on 10/1/2004; the remainder of the state entered MISO on 4/1/2005.

[18] Partly entered PJM on 10/1/2004; the state wasn't fully integrated into PJM until 5/1/2005.

[19] Is only partly within PJM territory.

[20] Partly entered PJM on 10/1/2004; the state wasn't fully integrated into PJM until 4/1/2002.

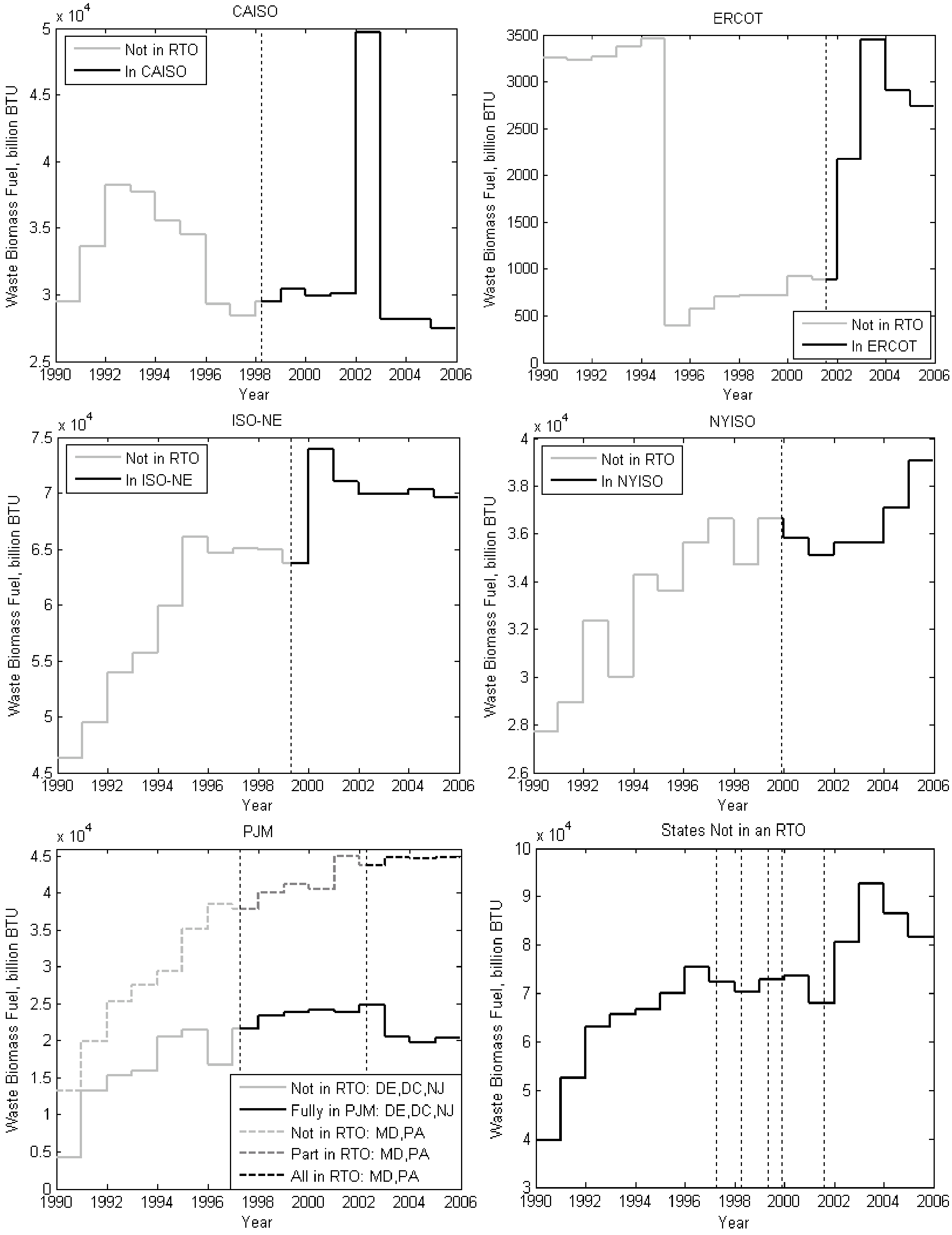

Figure 11. Waste biomass consumption for electric generation in each RTO with market start dates. The last plot shows consumption from all states that were not in RTOs by the end of 2005.

Figure 12 shows the growth of waste biomass from 1990-2006 separating those 14 states[21] that were fully within RTOs by the middle of 2002 from the 26 states[22] that had not joined RTOs by the end of 2005. The remaining 11 states[23] had either partly or fully joined RTOs by the end of 2005. Vertical dashed lines show the start dates of the five RTOs from Figure 11 and Figure 4; PJM's expansion in 2002 is not shown. Figure 12 shows slow, steady growth in waste biomass

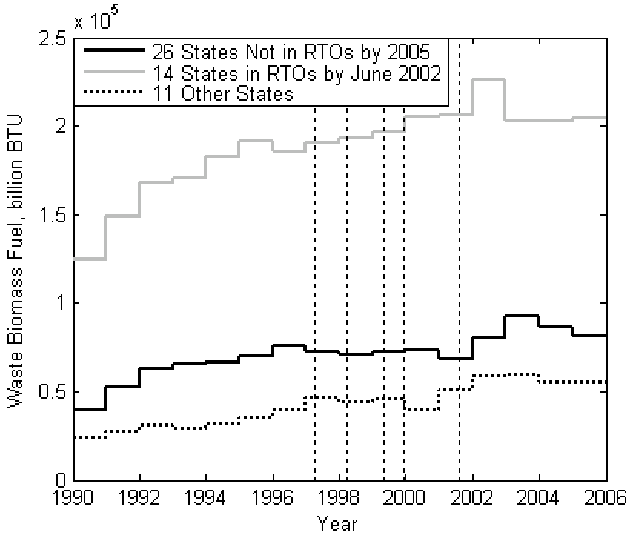

Figure 12. Comparison of wood biomass in RTO and non-RTO states, including DC.

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[21] This actually refers to 13 states and the District of Columbia: CA, CT, DC, DE, MA, MD, ME, NH, NJ, NY, PA, RI, TX, and VT.

[22] The 26 states are: AK, AL, AR, AZ, CO, FL, GA, HI, ID, KS, LA, MO, MS, NM, NV, OK, OR, SC, TN, UT, WA, and WY.

[23] The 11 other states are: IA, IL, IN, KY, MI, MN, MT, NC, ND, NE, OH, SD, VA, WI, and WV.

Table 5 shows the consumption of biomass waste for electricity generation in the top consuming states. Four states account for almost half the waste biomass consumption.

Table 5. Concentration of biomass wood consumption for electric generation in top producing states.

	Waste Biomass % in 2005		Date of RTO Entry
	Cumulative of Top Consumers	Individual State	
FL	19.0%	19.0%	Not in RTO
NY	30.5%	11.5%	12/1/1999
MA	40.1%	9.66%	5/1/1999
PA	49.5%	9.37%	4/1/1997[24]
CA	57.6%	8.07%	4/1/1998
CT	65.3%	7.73%	5/1/1999
NJ	71.3%	6.01%	4/1/1997
MD	75.1%	3.80%	4/1/1997
VA	78.7%	3.61%	10/1/2004[25]
MN	82.3%	3.55%	4/1/2005
MI	85.3%	3.06%	10/1/2004[26]
IL	87.8%	2.44%	5/1/2004[27]
ME	89.7%	1.90%	5/1/1999
WI	91.2%	1.57%	4/1/2005
HI	92.5%	1.30%	Not in RTO
NH	93.7%	1.15%	5/1/1999

4 Renewable Production as a Function of RTO Status

The graphical analysis comparing RTO with non-RTO states before and after establishing these RTOs does not make a case that RTOs promote renewables. We now turn to more formal statistical analysis to explore the relationships between renewables and RTO. For solar and geothermal, there is so little use outside a few states that a statistical analysis cannot contribute our sorting out the effect of RTOs.

4.1 Notes on Regression Methods

We use two different approaches to exploring the statistical relationship between membership in an RTO and the use of renewables. In one we build a model we regard as structural and fit it to the data. In the other we explore the relationship between the two variables of interest fitting a wide range of specifications that appear to be plausible in controlling for other factors that influence the use of renewables. We use "feasible generalized least squares" (FGLS) to estimate

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[24] Partly entered PJM on 10/1/2004; the state wasn't fully integrated into PJM until 4/1/2002.
[25] Partly entered PJM on 10/1/2004; the state wasn't fully integrated into PJM until 5/1/2005.
[26] Partly entered PJM on 10/1/2004; the remainder of the state entered MISO on 4/1/2005.
[27] Partly entered PJM on 5/1/2004; the remainder of the state entered MISO on 4/1/2005.

the structural model in order to correct for autocorrelation and heteroscedasticity in the residuals [26]. For exploration, we use both FGLS and ordinary least squares (OLS).

Data Transformation – All variables except the dummy variables have been centered and scaled so that the tranformed variables all have a mean of 0 and a standard deviation of 1[28]. This means that the signs and relative magnitudes of variable coefficients are meaningful, but that the absolute magnitudes of variable coefficients must be interpreted with care. In our regressions, a coefficient of 0.5 means that a change of one standard deviation in the right-hand variable is associated with a positive change of 0.5 standard deviations in the left-hand variable.

Principal Component Analysis – For some groups of input data that may be highly multicollinear such as biomass resource potential variables and state renewables policies, we have transformed these data into their principal components. We then use the principal components as independent variables in these regressions as discussed in Appendix A.

Autocorrelation – The assumption under OLS is that the errors (observed renewable generation minus the regression's predicted value) are independently, identically distributed. This assumption implies, among other things, that the observation of wind output from one year is assumed to be independent of the wind output from the previous year. This assumption is violated because most of the capacity installed last year will still be installed this year. Since the regression generates errors that are related to output, the systematic pattern in output leads to a systematic pattern in the error terms.

Heteroscedasticity – As noted in Section 3, wind, wood, and waste are concentrated in just a few states. This means that both the magnitude of generation outputs and the magnitude of variability in those outputs are much larger in some states than in others. Under OLS, this means that the large magnitude and variation in renewables output in California would skew the regression results severely.

Feasible Generalized Least Squares[29] – We run a regression on panel data using FGLS, which corrects both autocorrelation and heteroscedasticity [26].

Ordinary Least Squares – We run a variety of different regressions using OLS to explore the robustness of relationships in the data to many plausible specifications. These results are primarily for illustration however, because the OLS method does not account for autocorrelation or heteroscedasticity. These results must be interpreted only as a statistical exploration of the data.

We apply the FGLS method to the data on state outputs of wind, biomass wood, and biomass waste. The models for wood and biomass waste are similar to that for wind.

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[28] The mean and standard deviation are taken for each variable. For each datum, the mean is subtracted and the result is divided by the standard deviation. The transformed data then have a mean of zero and standard deviation of one.

[29] We use the econometrics program Stata to implement these methods. The Stata command used for FGLS with panel data is **`xtgls`** with options **`panels(heteroskedastic)`** and **`corr(psar1)`** implemented to account for heteroscedasticity and autocorrelation respectively [27].

4.2 Wind Results

RTO Significance

We fit Equation (1) to the data, where the left-hand variable is the change in wind output from year *t* - 1 to year *t*, divided by total state generation in year 2005. Because we are predicting the *change* in wind, we lose the 1990 observation, with 1991 representing the change from 1990, etc. to 2005; our yearly dummy variables span 1992-2005, since the first one must be excluded. The change in wind from one year to the next is a function of the variables introduced in Table 1 as follows.

RTO	The number of years that the state has been at least partly in an RTO is included to test whether being a member of an RTO induces more renewables.
GSP	Gross state product per capita, since wind would be selected on environmental-sustainability grounds, not because it is the cheapest source
MWh	The total amount of electricity generated in the state, since larger states should find it easier to incorporate wind into their grid.
Price	The price of electricity in the state, since the higher the price, the more attractive wind is.
Dem	The proportion of the major-party votes won by the democratic presidential candidate in 2004, since the liberals are more likely to favor the environmentally-sustainable electricity source.
WindPot	The potential wind resource in each state, since the states with the greatest wind resource are likely to have the lowest cost.
PolicyP	The eight transformed variables that characterize state incentives to develop wind such as tax benefits and renewable portfolio standards.
YT	Dummy variables for each year 1992- 2005. Year 1992 is 1 in each state for 1992 and 0 for other years; 1993 is 1 in each state for 1993 and 0 otherwise, etc. These dummy variables account for any factor that is common to all states in each particular year, such as the expiration of the federal production tax credit.

We hypothesize that the estimated coefficients of the variables will be positive. Some of the yearly dummy variables have negative coefficient, as might some policy variables.

$$(1)\quad \frac{\Delta Wind}{MWh_{05}} = \alpha_0 + \alpha_R RTO + \alpha_G GSP + \alpha_M MWh + \alpha_{\$} Price + \alpha_D Dem + \alpha_P WindPot + \sum_{p=1}^{8} \alpha_p PolicyP + \sum_{T=1992}^{2005} \alpha_y YT$$

Table 6 displays the primary results. Parameters significant at the $p \leq 0.05$ level are in bold. As hypothesized, the estimated coefficients of state income, electricity generation, electricity price, Democratic vote, and wind potential are all positive, but none attain statistical significance. As hypothesized, the state policy variables are statistically significant as a group with F(8, 691) = 5.323, p-value = 0.000. Likewise, the yearly dummy variables are significant as a group with F(14, 691) = 2.183, p-value = 0.007.

Contrary to our hypothesis, the RTO status variable is negative and significant. *The coefficient of RTO continues to be negative and significant for most alternative specifications as elaborated below:* replacing *RTO* with *RTOFull* and *RTOPart*, we find that signs and magnitudes of the other significant predictors do not change and that both of these other variables are significant negative predictors. The size of the negative relationship is small; the *RTO* coefficient of -0.0661 indicates that 1.57 years in an RTO (one standard deviation of *RTO*) predicts that the normalized growth rate of wind would be reduced by 6.61% of a standard deviation.

Table 6. FGLS results for regressing wind output on RTO status and other possible structural variables.

FGLS Model Regression on Wind			
Estimated Covariances	48	Number of Groups	48
Estimated Autocorrelations	48	Time Periods	15
Estimated Coefficients	29	Wald χ^2(28)	62.7
Number of Observations	720	Prob > χ^2	0.0002

Variable	Coefficient Estimate	Standard Error	z	P > |z|	95% Confidence Interval	
RTO	**-0.0661**	**0.0151**	**-4.39**	**0.000**	**-0.0956**	**-0.0366**
GSP	0.0306	0.0263	1.16	0.245	-0.0210	0.0822
MWh	0.0281	0.0388	0.72	0.469	-0.0480	0.1042
Price	0.0108	0.0326	0.33	0.740	-0.0530	0.0746
Dem	0.0130	0.0593	0.22	0.826	-0.1032	0.1292
WindPot	0.0762	0.0522	1.46	0.145	-0.0263	0.1786
*Policy*1	0.0173	0.0363	0.48	0.633	-0.0538	0.0885
***Policy*2**	**0.0730**	**0.0325**	**2.25**	**0.025**	**0.0093**	**0.1367**
***Policy*3**	**0.0957**	**0.0330**	**2.90**	**0.004**	**0.0310**	**0.1604**
*Policy*4	0.0118	0.0367	0.32	0.749	-0.0602	0.0837
*Policy*5	-0.0322	0.0311	-1.04	0.300	-0.0932	0.0288
***Policy*6**	**0.0824**	**0.0395**	**2.08**	**0.037**	**0.0049**	**0.1598**
*Policy*7	0.0267	0.0384	0.69	0.487	-0.0486	0.1020
*Policy*8	0.0512	0.0318	1.61	0.108	-0.0111	0.1135
*Y*1992	-0.0014	0.0328	-0.04	0.966	-0.0656	0.0629
*Y*1993	-0.0016	0.0422	-0.04	0.970	-0.0843	0.0811
*Y*1994	-0.0009	0.0474	-0.02	0.984	-0.0939	0.0920
*Y*1995	0.0003	0.0506	0.01	0.995	-0.0989	0.0995
*Y*1996	0.0082	0.0530	0.15	0.878	-0.0957	0.1120
*Y*1997	0.0194	0.0548	0.35	0.723	-0.0880	0.1269
*Y*1998	0.0532	0.0573	0.93	0.353	-0.0592	0.1655
*Y*1999	0.0965	0.0609	1.58	0.113	-0.0228	0.2158
***Y*2000**	**0.1327**	**0.0655**	**2.03**	**0.043**	**0.0044**	**0.2610**
***Y*2001**	**0.1716**	**0.0697**	**2.46**	**0.014**	**0.0349**	**0.3082**
***Y*2002**	**0.2271**	**0.0781**	**2.91**	**0.004**	**0.0739**	**0.3802**
***Y*2003**	**0.2447**	**0.0856**	**2.86**	**0.004**	**0.0771**	**0.4124**
***Y*2004**	**0.3045**	**0.0945**	**3.22**	**0.001**	**0.1193**	**0.4898**
***Y*2005**	**0.3073**	**0.1052**	**2.92**	**0.003**	**0.1011**	**0.5134**
Constant	-0.1021	0.0530	-1.93	0.054	-0.2059	0.0017

Individual State Policies

To explore the effects of state renewables policies, we replaced the transformed state policy variables with the number of years in effect for each of the actual 19 policies, as shown in Table 7. For example, a state with a renewable portfolio standard would have a 1 for this variable while states without this policy would have a zero. As measured by the Wald χ^2 statistic, this regression is better than that in Table 6. The RTO coefficient is half as large and loses statistical significance. Two of the structural variables change sign, although neither passed the test for statistical significance under either regression. The statistically significant state programs associated with renewables are rebates, loan programs, net metering, required green power offering, and renewable portfolio standards. Sales tax incentives have a significant negative association. Corporate tax incentives are almost significant. The other 12 state programs are not significant.

For each of the significant state policies, we look into the possibility that multicollinearity could be causing us to find spurious correlation due to multicollinearity among state policies.

- Sales tax incentives are collinear with corporate tax incentives (with correlation coefficient $\rho = 0.4811$) and net metering ($\rho = 0.3310$), when excluding corporate tax incentives and net metering from the regression, the sales tax incentive is still negative but no longer significant ($p = 0.500$). When sales tax incentives are excluded, corporate tax incentives is no longer anywhere close to significant ($p = 0.898$).
- Rebate programs are not collinear with the other state policies.
- Although loan programs are collinear with some other policies, with correlation coefficients as high as 0.3390 with interconnection standards, it is only highly collinear with other state policies that have positive coefficients. This means that if those other state policies are excluded from the regression, loan programs appear to be *more* significantly positive.
- Net metering is positively collinear with several other state policies listed here. Excluding the other significant policies, or even all of the policies, makes net metering appear *more* significantly positive because of the positive associations.
- Required green power offering is collinear with net metering ($\rho = 0.3052$). Because they have the same sign, when one is excluded the other becomes *more* significant.
- RPS is collinear with net metering ($\rho = 0.490$). Because they have the same sign, when one is excluded the other becomes *more* significant.

Based on these observations, we believe that the positive and negative associations between corporate and sales tax incentives are spurious. We do believe that the associations between wind and rebate programs, loan programs, net metering, required green power offering, and RPSes are real.

Table 7. Wind regression with all 19 state variables.

FGLS Model Regression on Wind with 19 State Policy Variables			
Estimated Covariances	48	Number of Groups	48
Estimated Autocorrelations	48	Time Periods	15
Estimated Coefficients	40	Wald $\chi^2(28)$	97.1
Number of Observations	720	Prob > χ^2	0.0000

Variable	Coefficient Estimate	Standard Error	z	P > |z|	95% Confidence Interval	
RTO	-0.0306	0.0182	-1.68	0.093	-0.0663	0.0051
GSP	-0.0348	0.0445	-0.78	0.434	-0.1219	0.0524
MWh	0.0156	0.0338	0.46	0.644	-0.0506	0.0819
Price	-0.0037	0.0322	-0.12	0.908	-0.0668	0.0594
Dem	0.0229	0.0494	0.46	0.643	-0.0739	0.1198
WindPot	0.0512	0.0414	1.24	0.217	-0.0300	0.1324
Personal Tax Incentives	-0.0634	0.0462	-1.37	0.170	-0.1538	0.0271
Corporate Tax Incentives	0.1114	0.0574	1.94	0.052	-0.0011	0.2238
Sales Tax Incentives	**-0.1085**	**0.0448**	**-2.42**	**0.016**	**-0.1964**	**-0.0206**
Property Tax Incentives	0.0007	0.0328	0.02	0.984	-0.0636	0.0649
Rebate Programs	**0.0939**	**0.0272**	**3.45**	**0.001**	**0.0406**	**0.1473**
Grant Programs	-0.0261	0.0443	-0.59	0.556	-0.1128	0.0607
Loan Programs	**0.0986**	**0.0454**	**2.17**	**0.030**	**0.0096**	**0.1876**
Industry Recruitment	-0.0242	0.0364	-0.67	0.505	-0.0956	0.0471
Bond Programs	0.0018	0.0079	0.23	0.817	-0.0136	0.0173
Production Incentives	-0.0076	0.0161	-0.47	0.637	-0.0392	0.0240
Public Benefits Fund	-0.0379	0.0329	-1.15	0.249	-0.1023	0.0265
Generation Mix Disclosure	-0.0283	0.0294	-0.96	0.335	-0.0859	0.0292
Net Metering	**0.0902**	**0.0428**	**2.11**	**0.035**	**0.0063**	**0.1741**
Interconnection Standards	0.0606	0.0391	1.55	0.121	-0.0161	0.1373
Equipment Certification	-0.0499	0.0351	-1.42	0.155	-0.1188	0.0189
Construction and Design Codes	0.0496	0.0317	1.56	0.118	-0.0126	0.1118
Green Power Purchasing	-0.0101	0.0220	-0.46	0.646	-0.0533	0.0330
Required Green Power Offering	**0.1703**	**0.0579**	**2.94**	**0.003**	**0.0568**	**0.2838**
Renewable Portfolio Standard	**0.0706**	**0.0284**	**2.49**	**0.013**	**0.0150**	**0.1263**
Y1992	-0.0015	0.0312	-0.05	0.962	-0.0627	0.0598
Y1993	-0.0017	0.0394	-0.04	0.965	-0.0790	0.0755
Y1994	0.0005	0.0439	0.01	0.991	-0.0855	0.0865
Y1995	0.0011	0.0466	0.02	0.981	-0.0903	0.0925
Y1996	0.0081	0.0491	0.17	0.868	-0.0882	0.1044
Y1997	0.0200	0.0524	0.38	0.703	-0.0828	0.1228
Y1998	0.0382	0.0568	0.67	0.502	-0.0731	0.1494
Y1999	0.0683	0.0616	1.11	0.268	-0.0524	0.1890

*Y*2000	0.0879	0.0660	1.33	0.182	-0.0413	0.2172
*Y*2001	0.1097	0.0690	1.59	0.112	-0.0254	0.2449
*Y*2002	0.1349	0.0748	1.80	0.071	-0.0117	0.2816
*Y*2003	0.1290	0.0811	1.59	0.112	-0.0299	0.2879
*Y*2004	0.1415	0.0889	1.59	0.112	-0.0329	0.3158
*Y*2005	0.1062	0.0971	1.09	0.274	-0.0840	0.2965
Constant	-0.0867	0.0571	-1.52	0.129	-0.1987	0.0253

Exploration of Alternative Specifications

To explore the robustness of the negative association of RTO with renewables, we estimated a number of different specifications. The first was to rerun the regression in Table 6 excluding the 6 states with no wind potential[30]. Since these states have no possibility of generating electricity from wind, they could be argued to be irrelevant to the analysis. The regression, shown in Appendix B, continues to have RTO as a negative significant coefficient. A second run excluded the 25 states that had no generation from wind in 2005[31]. Some of these states may be on the brink of constructing wind turbines and others may have considered and rejected wind turbines. Thus, these states represent a number of different cases, but all are lumped into zero wind. We reestimated the regression in Table 6 with just the states that had at least some wind generation. Again the results are not much different from the regression with all 48 states, as shown in the appendix. The RTO coefficient is still negative and significant.

Within the FGLS framework, we changed the state policy variables from the number of years a state had these policies to a dummy variable indicating whether they had these policies. The only substantial change was that the wind potential variable became statistically significant. Another variation was to change the RTO variable so that instead of the number of years a state was in an RTO, we used a dummy variable indicating whether it was in an RTO. This specification used principle components for the state policy variables. The principal effect of this change in the RTO specification was to make the RTO coefficient statistically insignificant, although it continued to have a negative sign. One other variation was to estimate a model whether RTO status was represented as a dummy variable and all 19 state policy variables were used. In this regression, the RTO coefficient was positive but was not statistically significant. We observe that there is a high correlation between the dummy variable for RTO membership and some of the 19 state policy variables, although that problem is eliminated when using principle components to represent the state policy variables.

We also estimated a number of different specifications for wind using OLS. In Appendix C.1 we show summary results from 48 different regressions including every permutation of the following:

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[30] AL, FL, IN, KY, LA, and MS.

[31] AL, AR, AZ, CT, DE, FL, GA, ID, IN, KY, LA, MA, MD, ME, MO, MS, MT, NC, NH, NJ, NV, RI, SC, UT, and VA.

Dependent Variable Specification – We examine six ways of measuring wind output: absolute output *Wind* in MWh, as a percent of total MWh output %*Wind*, change in MWh of wind output from the previous year Δ*Wind*, change normalized by total MWh Δ*Wind*/*MWh*, change normalized by year 2005 MWh $\Delta Wind/MWh_{05}$, and change in percentage wind Δ(%*Wind*). Some of these options for specifying the independent variable partially mitigate the autocorrelation problem because they deal with the change in wind output rather than the value at any one time.

RTO Status Specification – We specify RTO status in one of the four ways. In two of the ways we use the number of years with a particluar RTO status with *RTO* or the combination of the two variables *RTOFull* and *RTOPart*. In the remaining two ways we use the analogous dummy variables for status.

Lagged Left-Hand Variable – We run the regressions in two ways. Once by excluding any lagged variable and once by including the value of the left-hand variable that applied in the previous year.

Summary results from these 48 specifications are contained in Appendix C.1. A summary of the regression results indicates the robustness of our finding of a negative correlation between RTO membership and wind.

Of these specifications we find the following summary results relating to the possible relationship between wind and RTO status.

- In 3 specifications, the estimated coefficient of RTO is positive and significant. These estimates are unreliable because the three specifications have the worst problems with autocorrelation. We restimated these specifications using FGLS to correct for autocorrelation and heterskedasticity. When the problems with the residuals are corrected, two of the three regressions change in that the positive coefficient of RTO loses statistical significance. Thus, after correcting for problems in the residuals, only one regression has a positive, significant coefficient of RTO.
- In 24 specifications, the estimated coefficient of RTO is negative and significant. Various problems make some of these estimates unreliable.
- In 21 specifications, the estimated coefficients are not statistically significant, although most are negative.

Given the range of specifications for the relationship between wind generation and membership in an RTO, we think it unlikely that a plausible alternative specification with these data that performs well on measures of autocorrelation and heteroscedasticity would find a positive relationship that was statistically significant. From these results we see that the data do not show evidence of a positive association between RTO membership and wind output, controlling for other factors. The data suggest rather that there is a negative relationship between the two, although we cannot assert that the relationship is causal.

4.3 Solar and Geothermal

Our analysis of solar and geothermal indicated that too few states have developed these resources to conclude whether there was a relationship between their development and membership in an RTO.

4.4 Wood Biomass Results

RTO Significance

Investigating the relationship for wood biomass, we modified Equation (1) slightly by substituting variables for the size of the biomass resource for the size of the wind resource to get Equation (2).

$$(2) \quad \frac{\Delta Wood}{MWh_{05}} = \alpha_0 + \alpha_R RTO + \alpha_G GSP + \alpha_M MWh + \alpha_\$ Price + \alpha_D Dem + \sum_{b=1}^{5} \alpha_b BioResb + \sum_{p=1}^{8} \alpha_p PolicyP + \sum_{T=1992}^{2005} \alpha_y YT$$

Figure 8 displays the results from running the FGLS regression. The model does not fit the data; the Wald χ^2 test is not significant. None of the other variables are significant, although they are positive except for *GSP*. The estimated coefficient of RTO is negative and insignificant. Even after dropping all of the other variables, RTO status does not show a statistically significant relationship with wood. This is probably because, as observed in Section 3, the variability of wood output over time is much larger than any trend we could observe within any of the RTOs.

Table 8. FGLS results regressing wood for electric generation on RTO status and other possible causal variables.

FGLS Model Regression on Wood			
Estimated Covariances	48	Number of Groups	48
Estimated Autocorrelations	48	Time Periods	15
Estimated Coefficients	33	Wald $\chi^2(28)$	5.68
Number of Obs	720	Prob > χ^2	1.000

Variable	Coefficient Estimate	Standard Error	z	P > |z|	95% Confidence Interval	
RTO	-0.0017	0.0075	-0.22	0.824	-0.0164	0.0131
GSP	-0.0070	0.0246	-0.28	0.777	-0.0552	0.0413
MWh	0.0050	0.0230	0.22	0.827	-0.0400	0.0501
Price	0.0087	0.0194	0.45	0.655	-0.0294	0.0468
Dem	0.0114	0.0196	0.58	0.561	-0.0271	0.0499
*BioRes*1	0.0021	0.0133	0.16	0.874	-0.0239	0.0281
*BioRes*2	0.0000	0.0100	0.00	0.998	-0.0196	0.0197
*BioRes*3	0.0001	0.0151	0.01	0.993	-0.0295	0.0297
*BioRes*4	0.0016	0.0116	0.14	0.888	-0.0211	0.0244
*BioRes*5	0.0090	0.0168	0.53	0.593	-0.0239	0.0418
*Policy*1	-0.0021	0.0114	-0.19	0.852	-0.0245	0.0202
*Policy*2	-0.0004	0.0101	-0.04	0.967	-0.0201	0.0193
*Policy*3	-0.0047	0.0144	-0.33	0.741	-0.0329	0.0234
*Policy*4	0.0075	0.0155	0.48	0.628	-0.0228	0.0378
*Policy*5	-0.0008	0.0122	-0.06	0.950	-0.0247	0.0232
*Policy*6	0.0069	0.0168	0.41	0.682	-0.0260	0.0398
*Policy*7	-0.0032	0.0149	-0.21	0.832	-0.0325	0.0261
*Policy*8	0.0031	0.0112	0.27	0.784	-0.0190	0.0251
*Y*1992	0.0154	0.0340	0.45	0.651	-0.0513	0.0820
*Y*1993	0.0152	0.0379	0.40	0.689	-0.0592	0.0895
*Y*1994	-0.0048	0.0396	-0.12	0.904	-0.0824	0.0728
*Y*1995	-0.0152	0.0409	-0.37	0.710	-0.0954	0.0650
*Y*1996	0.0078	0.0426	0.18	0.856	-0.0758	0.0913
*Y*1997	0.0042	0.0449	0.09	0.926	-0.0839	0.0922
*Y*1998	-0.0015	0.0478	-0.03	0.975	-0.0952	0.0922
*Y*1999	-0.0069	0.0509	-0.14	0.892	-0.1067	0.0928
*Y*2000	0.0018	0.0533	0.03	0.973	-0.1027	0.1063
*Y*2001	0.0028	0.0536	0.05	0.958	-0.1022	0.1078
*Y*2002	0.0294	0.0562	0.52	0.601	-0.0808	0.1395
*Y*2003	0.0303	0.0574	0.53	0.598	-0.0823	0.1428
*Y*2004	0.0238	0.0597	0.40	0.690	-0.0933	0.1409
*Y*2005	0.0266	0.0617	0.43	0.667	-0.0943	0.1475
Constant	-0.0470	0.0343	-1.37	0.170	-0.1142	0.0201

Exploration of Alternative Specifications

Again we have used OLS to estimate a wide range of plausible specifications with different characterizations of wood consumption for electric generation as the dependent variable and different explanatory variables. In Appendix C.2 we show summary results from 48 different regressions including every permutation of the following:

Dependent Variable Specification – We examine six ways of measuring wood biomass consumption for electric power production; consumption *Wood* in BTU, normalized by total MWh output *Wood/MWh*, change in wood consumption from the previous year $\Delta Wood$, change normalized by total MWh $\Delta Wood/MWh_T$, change normalized by year 2005 MWh $\Delta Wood/MWh_{05}$, and change in normalized wood consumption $\Delta(Wood/MWh)$. Some of these options for specifying the independent variable will mitigate the autocorrelation problem because they deal with the change in output rather than the value at any one time.

RTO Status Specification – We specify RTO status in one of the four ways. In two of the ways we use the number of years with a particluar RTO status with *RTO* or the combination of the two variables *RTOFull* and *RTOPart*. In the remaining two ways we use the analogous dummy variables for status.

Lagged Left-Hand Variable – We run the regressions in two ways. Once by excluding any lagged variable and once by including the value of the left-hand variable that applied in the previous year.

Of these specifications we find the following summary results relating to the possible relationship between wood and RTO status.

- In 8 specifications, the estimated coefficient of RTO is positive and statistically significant. These results are unreliable because of autocorrelation.
- Under no specifications is the estimated coefficient of RTO negative and significant.
- In 40 specifications, the estimated coefficient of RTO is not statistically significant.

The regressions show that there *may be* a positive association between RTOs and the use of wood biomass for production of electricity, but this is inconclusive because the relationship is not statistically significant.

4.5 Waste Biomass Results

RTO Significance

Because the biomass resource variables are indicators of both waste biomass and wood biomass as discussed in Section 2, we have used the same explanation variables for waste biomass as for wood biomass.

$$(3)\quad \frac{\Delta Waste}{MWh_{05}} = \alpha_0 + \alpha_R RTO + \alpha_G GSP + \alpha_M MWh + \alpha_\$ Price + \alpha_D Dem + \sum_{b=1}^{5} \alpha_b BioResb + \sum_{p=1}^{8} \alpha_p PolicyP + \sum_{T=1992}^{2005} \alpha_y YT$$

Table 9 displays the results from the FGLS regression Once again, the model does not pass the Wald χ^2 test for significance. However, the coefficients of the explanatory variables remain positive and total generation, electricity price, and one of the biomass resources are statistically significant. The estimated coefficient of RTO status remains negative and is bordering on significant. When non-significant variables are omitted one at a time until only significant variables remain[32], RTO status does become a significant negative predictor[33].

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[32] In this case the remaining variables are *RTO*, *Dem,* and *BioResb*. The coefficient on *Dem* is positive and it has p-value 0.001. The Wald χ^2 statistic then shows model significance with p-value = 0.0002.

[33] With p-value 0.038.

Table 9. FGLS results regressing waste for electric generation on RTO status and other possible causal variables.

FGLS Model Regression on Waste			
Estimated Covariances	48	Number of Groups	48
Estimated Autocorrelations	48	Time Periods	15
Estimated Coefficients	33	Wald $\chi^2(28)$	31.92
Number of Obs	720	Prob > χ^2	0.471

Variable	Coefficient Estimate	Standard Error	z	P > |z|	95% Confidence Interval	
RTO	-0.0202	0.0110	-1.83	0.068	-0.0418	0.0015
GSP	0.0107	0.0187	0.57	0.569	-0.0261	0.0474
MWh	**0.0426**	**0.0193**	**2.21**	**0.027**	**0.0048**	**0.0804**
Price	**0.0418**	**0.0212**	**1.97**	**0.048**	**0.0003**	**0.0834**
Dem	0.0150	0.0183	0.82	0.413	-0.0209	0.0510
*BioRes*1	0.0158	0.0123	1.28	0.201	-0.0084	0.0399
***BioRes*2**	**-0.0274**	**0.0106**	**-2.60**	**0.009**	**-0.0481**	**-0.0067**
*BioRes*3	-0.0129	0.0097	-1.33	0.184	-0.0320	0.0061
*BioRes*4	0.0052	0.0093	0.56	0.576	-0.0130	0.0235
*BioRes*5	-0.0023	0.0119	-0.19	0.848	-0.0255	0.0210
*Policy*1	-0.0124	0.0134	-0.92	0.357	-0.0387	0.0140
*Policy*2	0.0114	0.0120	0.96	0.339	-0.0120	0.0349
*Policy*3	0.0164	0.0130	1.26	0.209	-0.0092	0.0419
*Policy*4	0.0007	0.0148	0.05	0.962	-0.0282	0.0296
*Policy*5	0.0043	0.0152	0.28	0.778	-0.0255	0.0341
*Policy*6	0.0057	0.0137	0.42	0.675	-0.0211	0.0326
*Policy*7	-0.0169	0.0127	-1.33	0.182	-0.0417	0.0079
*Policy*8	-0.0131	0.0113	-1.16	0.245	-0.0352	0.0090
*Y*1992	0.0064	0.0294	0.22	0.829	-0.0513	0.0640
*Y*1993	-0.0220	0.0332	-0.66	0.508	-0.0870	0.0431
*Y*1994	0.0035	0.0346	0.10	0.919	-0.0643	0.0714
*Y*1995	0.0027	0.0357	0.08	0.939	-0.0672	0.0726
*Y*1996	-0.0015	0.0369	-0.04	0.967	-0.0739	0.0708
*Y*1997	-0.0025	0.0383	-0.06	0.949	-0.0775	0.0726
*Y*1998	-0.0128	0.0397	-0.32	0.747	-0.0907	0.0651
*Y*1999	-0.0124	0.0413	-0.30	0.765	-0.0934	0.0686
*Y*2000	-0.0030	0.0428	-0.07	0.944	-0.0869	0.0808
*Y*2001	-0.0050	0.0427	-0.12	0.906	-0.0887	0.0786
*Y*2002	0.0029	0.0443	0.07	0.947	-0.0840	0.0898
*Y*2003	-0.0233	0.0454	-0.51	0.607	-0.1123	0.0656
*Y*2004	-0.0235	0.0471	-0.50	0.618	-0.1159	0.0689
*Y*2005	-0.0407	0.0490	-0.83	0.406	-0.1368	0.0554
Constant	0.0078	0.0310	0.25	0.802	-0.0530	0.0686

Exploration of Alternative Specifications

Again we have used OLS to estimate a wide range of plausible specifications with different characterizations of waste consumption for electric generation as the dependent variable and different explanatory variables. In Appendix C.3 we show summary results from 48 different regressions including every permutation of the following:

Dependent Variable Specification – We examine six ways of measuring wood biomass consumption for electric power production; consumption *Wood* in BTU, normalized by total MWh output *Waste/MWh*, change in wood consumption from the previous year $\Delta Waste$, change normalized by total MWh $\Delta Waste/MWh_T$, change normalized by year 2005 MWh $\Delta Waste/MWh_{05}$, and change in normalized wood consumption $\Delta(Waste/MWh)$. Some of these options for specifying the independent variable will mitigate the autocorrelation problem because they deal with the change in output rather than the value at any one time.

RTO Status Specification – We specify RTO status in one of the four ways. In two of the ways we use the number of years with a particluar RTO status with *RTO* or the combination of the two variables *RTOFull* and *RTOPart*. In the remaining two ways we use the analogous dummy variables for status.

Lagged Left-Hand Variable – We run the regressions in two ways. Once by excluding any lagged variable and once by including the value of the left-hand variable that applied in the previous year.

Of these specifications we find the following summary results relating to the possible relationship between waste and RTO status.

- In 1 specification, the data show a significant, positive correlation between RTO membership and waste. This regression shows some of the worst autocorrelation.
- In 2 specifications, the data show a significant, negative correlation between RTO membership and geothermal. Each regression shows problematic autocorrelation.
- In 45 specifications, the data show no significant correlation between RTO membership and waste biomass. Some of these regressions have autocorrelation problems or low explanatory power, but many of them have neither problem.

Based on the results from the OLS and FGLS investigations, we find some weak evidence for a negative relationship between RTO membership and waste biomass, but the finding is not robust. Although we cannot say decisively whether there is or is not a *negative* relationship between RTOs and waste, these results show that there certainly is not a *positive* relationship.

5 Conclusions and Recommendations

The development of renewables began well before the RTOs were organized, although the use of wind grew rapidly after RTOs began. A feasible generalized least squares analysis of a structural model showed that, after accounting for factors known to influence wind development, the relationship between wind and RTO was negative and statistically significant. We explored a wide range of alternative specifications using both FGLS and ordinary least squares to explore a wide range of plausible specifications. In 48 regressions, the RTO coefficient was significantly positive under 3 specifications, significant and negative under 24 different specifications, and insignificant under 21 specifications. When the three regressions with positive, significant coefficients for RTO under OLS were reestimated using FGLS, only one continued to be statistically significant.

For solar and geothermal, too few states have developed these resources to allow a confident statement about the relationship between development of these renewables and membership in an RTO. For wood waste and biomass waste, the models did not fit the data well. Membership in an RTO was negatively correlated with development of these resources under FGLS, although the relationships are so weak that they do not pass significance tests. There is a hint of a positive relationship between electricity from wood and RTO membership.

We conclude that there is no evidence that membership in an RTO promoted the development of renewables. The statistical analysis indicates that membership in an RTO is negatively correlated with wind development, but we have no explanation as to why this would be true and so leave this result for further investigation.

6 Acknowledgements

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Appendix A Principal Components

The sets of raw data representing state renewables policies and biomass resource availability are highly multicollinear. To remedy the problems, we computed the principal components within each data set and kept a smaller number of principal components that explain most of the variation.

A.1 State Renewables Policy Data

Figure 13 shows the variance accounted for versus the number of principal components for state renewables policies. The variable is the number of years since 1990 that the policy has been in place. If a policy has been in place longer than 1990, only the length of time since 1990 is counted. We keep the top eight principal components from Figure 13 to use our regressions. Adding the next component would represent less than 4% of the variation in the data.

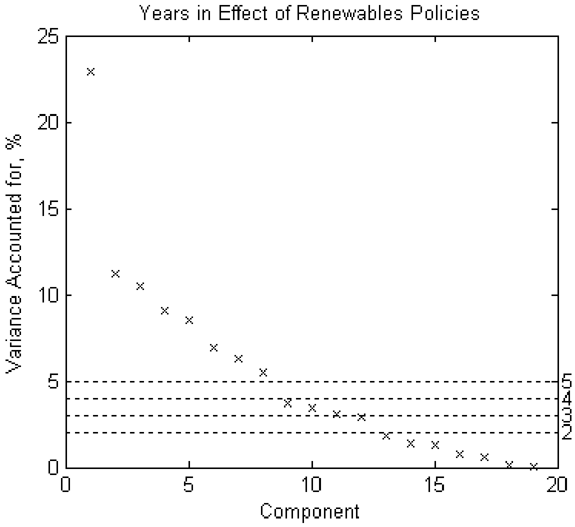

Figure 13. Variance accounted for versus number of principal components, years with state renewables policies.

A.2 Biomass Resource Data

Figure 14 shows variance accounted for versus number of principal components for the 28 biomass resource variables available by state. We keep the top five principal components to use in our regressions. The next component explains roughly another 2% of the variation in the data.

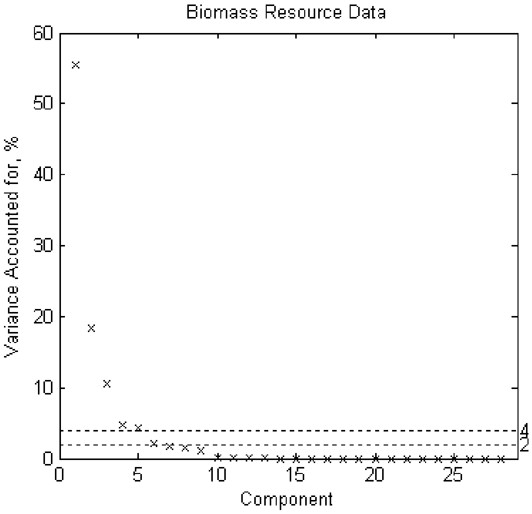

Figure 14. Variance accounted for versus number of principal components, biomass resource variables.

Appendix B FGLS Regressions without the No-Wind States

Table 8 and Table 9 show the wind regression from Table 6 after excluding the 6 states with no wind potential and the 25 states with no wind output by 2005 respectively.

Table 8. Wind Regression from Table 6 after removing states with no wind potential[34].

FGLS Model Regression on Wind			
Estimated Covariances	42	Number of Groups	42
Estimated Autocorrelations	42	Time Periods	15
Estimated Coefficients	29	Wald χ^2(28)	88.2
Number of Obs	630	Prob > χ^2	0.0000

Variable	Coefficient	Standard Error	z	P > |z|	95% Interval	
RTO	**-0.0971**	**0.0172**	**-5.65**	**0.000**	**-0.1307**	**-0.0634**
GSP	0.0567	0.0307	1.85	0.065	-0.0035	0.1169
MWh	0.0247	0.0414	0.60	0.552	-0.0565	0.1058
Price	0.0224	0.0343	0.65	0.514	-0.0448	0.0897
Dem	-0.0180	0.0631	-0.29	0.775	-0.1417	0.1057
WindPot	0.0457	0.0564	0.81	0.418	-0.0649	0.1563
*Policy*1	-0.0049	0.0372	-0.13	0.896	-0.0778	0.0681
_Policy_2	**0.1170**	**0.0380**	**3.08**	**0.002**	**0.0426**	**0.1914**
_Policy_3	**0.1635**	**0.0374**	**4.37**	**0.000**	**0.0902**	**0.2368**
_Policy_4	**0.1228**	**0.0524**	**2.34**	**0.019**	**0.0200**	**0.2256**
_Policy_5	**-0.1520**	**0.0516**	**-2.94**	**0.003**	**-0.2532**	**-0.0508**
_Policy_6	**0.1375**	**0.0464**	**2.96**	**0.003**	**0.0466**	**0.2284**
_Policy_7	**0.0881**	**0.0430**	**2.05**	**0.041**	**0.0038**	**0.1723**
*Policy*8	0.0213	0.0349	0.61	0.541	-0.0470	0.0896
*Y*1992	-0.0009	0.0422	-0.02	0.983	-0.0835	0.0818
*Y*1993	0.0003	0.0521	0.01	0.995	-0.1018	0.1024
*Y*1994	0.0006	0.0566	0.01	0.991	-0.1102	0.1115
*Y*1995	0.0004	0.0588	0.01	0.995	-0.1149	0.1157
*Y*1996	0.0093	0.0605	0.15	0.878	-0.1092	0.1279
*Y*1997	0.0239	0.0618	0.39	0.698	-0.0971	0.1450
*Y*1998	0.0742	0.0638	1.16	0.245	-0.0509	0.1993
_Y_1999	**0.1469**	**0.0676**	**2.17**	**0.030**	**0.0144**	**0.2793**
_Y_2000	**0.2111**	**0.0731**	**2.89**	**0.004**	**0.0678**	**0.3544**
_Y_2001	**0.2821**	**0.0791**	**3.57**	**0.000**	**0.1270**	**0.4372**
_Y_2002	**0.3887**	**0.0898**	**4.33**	**0.000**	**0.2127**	**0.5646**
_Y_2003	**0.4274**	**0.0996**	**4.29**	**0.000**	**0.2322**	**0.6227**
_Y_2004	**0.5557**	**0.1113**	**4.99**	**0.000**	**0.3377**	**0.7738**
_Y_2005	**0.5854**	**0.1256**	**4.66**	**0.000**	**0.3392**	**0.8315**
Constant	**-0.1548**	**0.0597**	**-2.59**	**0.009**	**-0.2718**	**-0.0378**

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[34] AL, FL, IN, KY, LA, and MS.

Table 9. Wind Regression from Table 6 after removing states with no wind output by 2005[35].

FGLS Model Regression on Wind			
Estimated Covariances	25	Number of Groups	25
Estimated Autocorrelations	25	Time Periods	15
Estimated Coefficients	29	Wald $\chi^2(28)$	145.5
Number of Obs	375	Prob > χ^2	0.0000

Variable	Coefficient Estimate	Standard Error	z	P > |z|	95% Confidence Interval	
RTO	**-0.1809**	**0.0386**	**-4.69**	**0.000**	**-0.2565**	**-0.1052**
GSP	**0.2008**	**0.0897**	**2.24**	**0.025**	**0.0250**	**0.3766**
MWh	-0.0082	0.0662	-0.12	0.901	-0.1379	0.1215
Price	0.0757	0.0886	0.85	0.393	-0.0979	0.2492
Dem	-0.0281	0.0992	-0.28	0.777	-0.2225	0.1663
WindPot	**0.0008**	**0.0003**	**2.29**	**0.022**	**0.0001**	**0.0014**
*Policy*1	-0.0276	0.0917	-0.30	0.764	-0.2073	0.1522
*Policy*2	0.0531	0.1025	0.52	0.605	-0.1478	0.2540
*Policy*3	0.1324	0.1547	0.86	0.392	-0.1707	0.4355
*Policy*4	-0.2145	0.3159	-0.68	0.497	-0.8336	0.4045
*Policy*5	0.2797	0.3809	0.73	0.463	-0.4669	1.0262
*Policy*6	0.1186	0.0800	1.48	0.138	-0.0382	0.2755
*Policy*7	0.0212	0.1082	0.20	0.845	-0.1910	0.2333
*Policy*8	0.0918	0.0704	1.30	0.193	-0.0463	0.2298
*Y*1992	-0.0485	0.1044	-0.46	0.643	-0.2531	0.1562
*Y*1993	-0.0371	0.1305	-0.28	0.776	-0.2928	0.2187
*Y*1994	-0.0503	0.1437	-0.35	0.726	-0.3319	0.2314
*Y*1995	-0.0807	0.1508	-0.54	0.592	-0.3762	0.2148
*Y*1996	-0.0793	0.1562	-0.51	0.612	-0.3854	0.2268
*Y*1997	-0.0832	0.1608	-0.52	0.605	-0.3985	0.2320
*Y*1998	-0.0052	0.1681	-0.03	0.975	-0.3347	0.3243
*Y*1999	0.1338	0.1790	0.75	0.455	-0.2170	0.4846
*Y*2000	0.1783	0.1822	0.98	0.328	-0.1789	0.5355
*Y*2001	0.2868	0.1904	1.51	0.132	-0.0864	0.6600
_Y_2002	**0.5914**	**0.2054**	**2.88**	**0.004**	**0.1889**	**0.9940**
_Y_2003	**0.5409**	**0.2157**	**2.51**	**0.012**	**0.1181**	**0.9636**
_Y_2004	**1.0117**	**0.2373**	**4.26**	**0.000**	**0.5466**	**1.4769**
_Y_2005	**0.8365**	**0.2597**	**3.22**	**0.001**	**0.3275**	**1.3455**
Constant	0.1251	0.1947	0.64	0.521	-0.2565	0.5066

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[35] AL, AR, AZ, CT, DE, FL, GA, ID, IN, KY, LA, MA, MD, ME, MO, MS, MT, NC, NH, NJ, NV, RI, SC, UT, and VA.

Appendix C RTO Significance under Other Specifications

This appendix contains summary results for various specifications of the OLS regression equations outlined in Section 4. The summary data contain only primary model results and results relating to the RTO status variables.

For each specification we report the Durbin-Watson statistic *d* as generalized for panel data [28]. A value very close to 2 indicates no autocorrelation; the closer the value is to 0, the greater the autocorrelation and the less reliable the regression results. We also report adjusted R^2 values.

The following results represent parsimonious models that include only significant predictors and yearly dummy variables. We have used the following algorithm for selecting significant predictor variables. Start with no predictor variables in the model. Add a variable if it has the lowest p-value for available additional variables and it has p-value < 0.05 from the t-test. Then subtract any variables that have p-values > 0.05 starting with the highest first. Stop adding and removing variables when no variables meet the criteria for adding or subtracting variables.

Variables representing RTO status are not only those introduced in Table 1 *RTO*, *RTOFull*, and *RTOPart* indicating the number of years that a state has had a particular RTO status, but also their analogous dummy variables δRTO, $\delta RTOFull$, and $\delta RTOPart$ that indicate the corresponding RTO status. When states changed RTO status mid-year, the dummy variables are given fractional values representing the fraction of the year that the state had a particular status.

For each renewables type, we have separated the results into two tables. The first table has results for all of the specifications that do not include a lagged left-hand variable in the regression. The second table contains the results under specifications that do include a lagged variable.

C.1 Additional Wind Specifications

Table 10. Regression results for 24 different model specifications predicting wind generation as a function of RTO status *without* using lagged variables.

Dependent Variable	**Overall Model Results**		***δRTOFull***		***δRTOPart***	
	Adj R^2	***d***	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Wind	0.6764	0.1020	0.1172	**0.0000**	-0.0225	0.2820
%	0.4722	0.2117	-0.1014	**0.0016**	-0.0492	0.0748
ΔWind	0.2558	1.5999	0.0663	0.0779	-0.0479	0.1519
ΔWind/MWh	0.1518	1.3935	-0.0607	0.1175	-0.0597	0.0934
ΔWind/MWh$_{05}$	0.1533	1.4029	-0.0660	0.0923	-0.0741	**0.0375**
Δ(%Wind)	0.1621	1.4222	-0.0724	0.0648	-0.0685	0.0540

Dependent Variable	**Overall Model Results**		***RTOFull***		***RTOPart***	
	Adj R^2	***d***	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Wind	0.6726	0.1017	0.0749	**0.0033**	-0.0424	**0.0497**
%	0.4925	0.2097	-0.1393	**0.0000**	-0.1367	**0.0000**
ΔWind	0.2558	1.5999	-0.0193	0.6092	-0.0446	0.1951
ΔWind/MWh	0.1823	1.4520	-0.1795	**0.0000**	-0.0991	**0.0079**
ΔWind/MWh$_{05}$	0.1798	1.4687	-0.1755	**0.0000**	-0.1025	**0.0061**
Δ(%Wind)	0.1906	1.4759	-0.1792	**0.0000**	-0.1045	**0.0049**

Dependent Variable	**Overall Model Results**		***δRTO***	
	Adj R^2	***d***	**Coefficient**	**p-value**
Wind	0.6727	0.1012	0.0885	**0.0006**
%	0.4737	0.2132	-0.1180	**0.0003**
ΔWind	0.2558	1.5999	0.0366	0.3386
ΔWind/MWh	0.1654	1.4317	-0.1367	**0.0017**
ΔWind/MWh$_{05}$	0.1635	1.4489	-0.1376	**0.0016**
Δ(%Wind)	0.1737	1.4559	-0.1418	**0.0010**

Dependent Variable	**Overall Model Results**		***RTO***	
	Adj R^2	***d***	**coefficient**	**p-value**
Wind	0.6694	0.1007	0.0391	0.1288
%	0.4917	0.2090	-0.1990	**0.0000**
ΔWind	0.2558	1.5999	-0.0397	0.2992
ΔWind/MWh	0.1833	1.4525	-0.2117	**0.0000**
ΔWind/MWh$_{05}$	0.1806	1.4695	-0.2097	**0.0000**
Δ(%Wind)	0.1914	1.4765	-0.2141	**0.0000**

Table 11. Regression results for 24 different model specifications predicting wind generation as a function of RTO status *including* lagged variables.

Dependent Variable	Overall Model Results		*δRTOFull*		*δRTOPart*	
	Adj R^2	*d*	Coefficient	p-value	Coefficient	p-value
Wind	0.9732	1.6883	0.0089	0.2120	-0.0085	0.1785
%	0.9063	1.6060	-0.0166	0.2071	-0.0176	0.1356
ΔWind	0.2568	1.6000	0.0663	0.0777	-0.0479	0.1516
ΔWind/MWh	0.1830	1.6790	-0.0498	0.2118	-0.0717	**0.0483**
$\Delta Wind/MWh_{05}$	0.1776	1.6663	-0.0465	0.2452	-0.0865	**0.0176**
Δ(%Wind)	0.1848	1.6695	-0.0480	0.2291	-0.0858	**0.0180**

Dependent Variable	Overall Model Results		*RTOFull*		*RTOPart*	
	Adj R^2	*d*	Coefficient	p-value	Coefficient	p-value
Wind	0.9732	1.6883	-0.0064	0.3750	-0.0071	0.2729
%	0.9081	1.6391	-0.0479	**0.0004**	-0.0236	0.0543
ΔWind	0.2568	1.6000	-0.0193	0.6090	-0.0446	0.1948
ΔWind/MWh	0.1991	1.6862	-0.1438	**0.0006**	-0.1030	**0.0066**
$\Delta Wind/MWh_{05}$	0.1920	1.6747	-0.1421	**0.0008**	-0.1077	**0.0047**
Δ(%Wind)	0.2040	1.6779	-0.1589	**0.0002**	-0.0995	**0.0091**

Dependent Variable	Overall Model Results		*δRTO*	
	Adj R^2	*d*	Coefficient	p-value
Wind	0.9732	1.6883	0.0037	0.6053
%	0.9062	1.6060	-0.0259	0.0555
ΔWind	0.2568	1.6000	0.0366	0.3382
ΔWind/MWh	0.1794	1.6764	-0.0753	**0.0649**
$\Delta Wind/MWh_{05}$	0.1717	1.6635	-0.0778	**0.0576**
Δ(%Wind)	0.1790	1.6664	-0.0789	**0.0531**

Dependent Variable	Overall Model Results		*RTO*	
	Adj R^2	*d*	coefficient	p-value
Wind	0.9732	1.6883	-0.0091	0.2029
%	0.9085	1.6369	-0.0565	**0.0001**
ΔWind	0.2568	1.6000	-0.0397	0.2989
ΔWind/MWh	0.1993	1.6856	-0.1802	**0.0000**
$\Delta Wind/MWh_{05}$	0.1919	1.6740	-0.1809	**0.0000**
Δ(%Wind)	0.2048	1.6775	-0.1930	**0.0000**

C.2 Additional Biomass Wood Specifications

Table 12. Regression results for 24 different model specifications predicting biomass wood consumption for electric generation as a function of RTO status *without* using lagged variables.

Dependent Variable	Overall Model Results		$\delta RTOFull$		$\delta RTOPart$	
	Adj R^2	*d*	Coefficient	p-value	Coefficient	p-value
Wood	0.4891	0.0773	0.0750	**0.0350**	-0.0015	0.9578
Wood/MWh	0.2994	0.0908	0.1490	**0.0002**	-0.0034	0.9138
$\Delta Wood$	0.0170	2.1854	0.0555	0.1758	-0.0070	0.8523
$\Delta Wood/MWh$	-0.0032	2.0056	0.0147	0.7111	-0.0083	0.8227
$\Delta \mathrm{Wood}/MWh_{05}$	0.0050	1.4993	0.0851	**0.0320**	-0.0036	0.9217
$\Delta(Wood/MWh)$	0.0019	1.4569	0.0776	0.0505	-0.0119	0.7469

Dependent Variable	Overall Model Results		*RTOFull*		*RTOPart*	
	Adj R^2	*d*	Coefficient	p-value	Coefficient	p-value
Wood	0.4898	0.0758	0.0809	**0.0198**	-0.0186	0.5315
Wood/MWh	0.2963	0.0868	0.1281	**0.0013**	-0.0152	0.6321
$\Delta Wood$	0.0170	2.1854	0.0626	0.1266	-0.0186	0.6217
$\Delta Wood/MWh$	-0.0032	2.0056	0.0240	0.5480	-0.0084	0.8208
$\Delta \mathrm{Wood}/MWh_{05}$	0.0002	1.4861	0.0620	0.1202	-0.0162	0.6611
$\Delta(Wood/MWh)$	0.0019	1.4569	0.0539	0.1766	-0.0147	0.6895

Dependent Variable	Overall Model Results		δRTO	
	Adj R^2	*d*	Coefficient	p-value
Wood	0.4867	0.0756	0.0625	0.0811
Wood/MWh	0.2919	0.0883	0.1237	**0.0020**
$\Delta Wood$	0.0170	2.1854	0.0497	0.2360
$\Delta Wood/MWh$	-0.0032	2.0056	0.0102	0.8019
$\Delta \mathrm{Wood}/MWh_{05}$	0.0002	1.4861	0.0762	0.0603
$\Delta(Wood/MWh)$	0.0019	1.4569	0.0693	0.0876

Dependent Variable	Overall Model Results		*RTO*	
	Adj R^2	*d*	coefficient	p-value
Wood	0.4867	0.0756	0.0613	0.0795
Wood/MWh	0.2918	0.0866	0.0999	**0.0108**
$\Delta Wood$	0.0170	2.1854	0.0478	0.2517
$\Delta Wood/MWh$	-0.0032	2.0056	0.0183	0.6518
$\Delta \mathrm{Wood}/MWh_{05}$	0.0002	1.4861	0.0498	0.2190
$\Delta(Wood/MWh)$	0.0019	1.4569	0.0430	0.2886

Table 13. Regression results for 24 different model specifications predicting biomass wood consumption for electric generation as a function of RTO status *including* lagged variables.

Dependent Variable	Overall Model Results		*δRTOFull*		*δRTOPart*	
	Adj R^2	*d*	Coefficient	p-value	Coefficient	p-value
Wood	0.9604	2.1730	0.0136	0.1072	-0.0017	0.8252
Wood/MWh	0.9452	2.0073	0.0034	0.7221	-0.0019	0.8267
Δ*Wood*	0.0164	2.1860	0.0555	0.1760	-0.0070	0.8524
Δ*Wood/MWh*	-0.0038	2.0066	0.0147	0.7112	-0.0083	0.8227
ΔWood/*MWh*$_{05}$	0.0058	1.4998	0.0851	**0.0319**	-0.0036	0.9217
Δ*(Wood/MWh)*	0.0027	1.4574	0.0776	0.0504	-0.0119	0.7468

Dependent Variable	Overall Model Results		*RTOFull*		*RTOPart*	
	Adj R^2	*d*	Coefficient	p-value	Coefficient	p-value
Wood	0.9604	2.1730	0.0153	0.0716	-0.0040	0.5958
Wood/MWh	0.9452	2.0073	0.0057	0.5531	-0.0019	0.8247
Δ*Wood*	0.0164	2.1860	0.0626	0.1267	-0.0186	0.6218
Δ*Wood/MWh*	-0.0038	2.0066	0.0240	0.5481	-0.0084	0.8209
ΔWood/*MWh*$_{05}$	0.0010	1.4866	0.0620	0.1200	-0.0162	0.6610
Δ*(Wood/MWh)*	0.0027	1.4574	0.0539	0.1764	-0.0147	0.6894

Dependent Variable	Overall Model Results		*δRTO*	
	Adj R^2	*d*	Coefficient	p-value
Wood	0.9604	2.1730	0.0120	0.1624
Wood/MWh	0.9452	2.0073	0.0023	0.8157
Δ*Wood*	0.0164	2.1860	0.0497	0.2361
Δ*Wood/MWh*	-0.0038	2.0066	0.0102	0.8019
ΔWood/*MWh*$_{05}$	0.0010	1.4866	0.0762	0.0601
Δ*(Wood/MWh)*	0.0027	1.4574	0.0693	0.0875

Dependent Variable	Overall Model Results		*RTO*	
	Adj R^2	*d*	coefficient	p-value
Wood	0.9604	2.1730	0.0115	**0.1759**
Wood/MWh	0.9452	2.0073	0.0043	**0.6604**
Δ*Wood*	0.0164	2.1860	0.0478	**0.2519**
Δ*Wood/MWh*	-0.0038	2.0066	0.0183	**0.6519**
ΔWood/*MWh*$_{05}$	0.0010	1.4866	0.0498	**0.2189**
Δ*(Wood/MWh)*	0.0027	1.4574	0.0430	**0.2884**

C.3 Additional Biomass Waste Specifications

Table 14. Regression results for 24 different model specifications predicting biomass waste consumption for electric generation as a function of RTO status *without* using lagged variables.

Dependent Variable	**Overall Model Results**		***δRTOFull***		***δRTOPart***	
	Adj R^2	***d***	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Waste	0.8368	0.1485	0.0114	0.5788	0.0606	**0.0001**
Waste /MWh	0.5449	0.1225	-0.0256	0.4353	0.0232	0.3738
Δ *Waste*	0.0361	2.3457	-0.0083	0.8378	0.0277	0.4603
Δ *Waste /MWh*	-0.0032	1.9637	-0.0535	0.1784	0.0178	0.6317
Δ *Waste /MWh*$_{05}$	0.0028	2.5983	0.0092	0.8172	0.0159	**0.6665**
Δ*(Waste /MWh)*	0.0122	2.2305	0.0037	0.9281	0.0136	0.7201
Dependent Variable	**Overall Model Results**		***RTOFull***		***RTOPart***	
	Adj R^2	***d***	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Waste	0.8355	0.1396	-0.0331	0.0951	0.0523	**0.0027**
Waste /MWh	0.5490	0.1240	-0.0886	**0.0054**	0.0150	0.5925
Δ *Waste*	0.0361	2.3457	-0.0403	0.3209	0.0189	0.6142
Δ *Waste /MWh*	-0.0032	1.9637	-0.0568	0.1552	0.0122	0.7405
Δ *Waste /MWh*$_{05}$	0.0028	2.5983	-0.0304	0.4461	0.0138	0.7091
Δ*(Waste /MWh)*	0.0122	2.2305	-0.0614	0.1351	0.0133	0.7247

Dependent Variable	**Overall Model Results**		***δRTO***	
	Adj R^2	***d***	**Coefficient**	**p-value**
Waste	0.8344	0.1394	0.0423	**0.0399**
Waste /MWh	0.5443	0.1225	-0.0084	0.8014
Δ *Waste*	0.0361	2.3457	0.0063	0.8797
Δ *Waste /MWh*	-0.0032	1.9637	-0.0431	0.2889
Δ *Waste /MWh*$_{05}$	0.0028	2.5983	0.0167	0.6812
Δ*(Waste /MWh)*	0.0122	2.2305	0.0106	0.8013
Dependent Variable	**Overall Model Results**		***RTO***	
	Adj R^2	***d***	**coefficient**	**p-value**
Waste	0.8337	0.1379	-0.0014	0.9430
Waste /MWh	0.5467	0.1234	-0.0718	**0.0276**
Δ *Waste*	0.0361	2.3457	-0.0274	0.5075
Δ *Waste /MWh*	-0.0032	1.9637	-0.0469	0.2486
Δ *Waste /MWh*$_{05}$	0.0028	2.5983	-0.0217	0.5918
Δ*(Waste /MWh)*	0.0122	2.2305	-0.0493	0.2382

Table 15. Regression results for 24 different model specifications predicting biomass waste consumption for electric generation as a function of RTO status *including* lagged variables.

Dependent Variable	**Overall Model Results**		***δRTOFull***		***δRTOPart***	
	Adj R^2	***d***	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Waste	0.9780	2.3454	-0.0013	0.8351	0.0043	0.4564
Waste /MWh	0.9374	1.9281	0.0004	0.9683	0.0046	0.6200
Δ Waste	0.0373	2.3458	-0.0083	0.8377	0.0277	0.4600
Δ Waste /MWh	-0.0019	1.9637	-0.0535	0.1781	0.0178	0.6315
Δ Waste /MWh$_{05}$	0.0040	2.5983	0.0092	0.8171	0.0159	0.6663
Δ(Waste /MWh)	0.0133	2.2305	0.0037	0.9281	0.0136	0.7199

Dependent Variable	**Overall Model Results**		***RTOFull***		***RTOPart***	
	Adj R^2	***d***	**Coefficient**	**p-value**	**Coefficient**	**p-value**
Waste	0.9780	2.3454	-0.0065	0.3075	0.0030	0.6048
Waste /MWh	0.9374	1.9281	-0.0031	0.7638	0.0052	0.5754
Δ Waste	0.0373	2.3458	-0.0403	0.3207	0.0189	0.6140
Δ Waste /MWh	-0.0019	1.9637	-0.0568	0.1549	0.0122	0.7403
Δ Waste /MWh$_{05}$	0.0040	2.5983	-0.0304	0.4458	0.0138	0.7089
Δ(Waste /MWh)	0.0133	2.2305	-0.0614	0.1349	0.0133	0.7245

Dependent Variable	**Overall Model Results**		***δRTO***	
	Adj R^2	***d***	**Coefficient**	**p-value**
Waste	0.9780	2.3454	0.0011	0.8683
Waste /MWh	0.9373	1.9281	0.0029	0.7877
Δ Waste	0.0373	2.3458	0.0063	0.8796
Δ Waste /MWh	-0.0019	1.9637	-0.0431	0.2886
Δ Waste /MWh$_{05}$	0.0040	2.5983	0.0167	0.6810
Δ(Waste /MWh)	0.0133	2.2305	0.0106	0.8012

Dependent Variable	**Overall Model Results**		***RTO***	
	Adj R^2	***d***	**coefficient**	**p-value**
Waste	0.9780	2.3454	-0.0046	0.4889
Waste /MWh	0.9373	1.9281	-0.0003	0.9769
Δ Waste	0.0373	2.3458	-0.0274	0.5072
Δ Waste /MWh	-0.0019	1.9637	-0.0469	0.2483
Δ Waste /MWh$_{05}$	0.0040	2.5983	-0.0217	0.5916
Δ(Waste /MWh)	0.0133	2.2305	-0.0493	0.2379