Year 2006 *Paper* 1015

The Future Trajectory of US CO2 Emissions: The Role of State vs. Aggregate Information

Maximilian Auffhammer
University of California, Berkeley

Ralf Steinhauser
University of California, Berkeley

The Future Trajectory of US CO2 Emissions: The Role of State vs. Aggregate Information

Abstract

This paper provides comparisons of a variety of time series methods for short run forecasts of the main greenhouse gas, carbon dioxide, for the United States, using a recently released state level data set from 1960-2001. We test the out-of-sample performance of univariate and multivariate forecasting models by aggregating state level forecasts versus forecasting the aggregate directly. We find evidence that forecasting the disaggregate series and accounting for spatial effects drastically improves forecasting performance under Root Mean Squared Forecast Error Loss. Based on the in-sample observations we attempt to explain the emergence of voluntary efforts by states to reduce greenhouse gas emissions. We find evidence that states with decreasing per capita emissions and a "greener" median voter are more likely to push towards voluntary cutbacks in emissions.

The Future Trajectory of US CO_2 Emissions: The Role of State vs. Aggregate Information*

Maximilian Auffhammer
University of California, Berkeley

Ralf Steinhauser
University of California, Berkeley

Date of this Draft:
March 1, 2006

Abstract

This paper provides comparisons of a a variety of time series methods for short run forecasts of the main greenhouse gas, carbon dioxide, for the United States, using a recently released state level data set from 1960-2001. We test the out-of-sample performance of univariate and multivariate forecasting models by aggregating state level forecasts versus forecasting the aggregate directly. We find evidence that forecasting the disaggregate series and accounting for spatial effects drastically improves forecasting performance under Root Mean Squared Forecast Error Loss. Based on the in-sample observations we attempt to explain the emergence of voluntary efforts by states to reduce greenhouse gas emissions. We find evidence that states with decreasing per capita emissions and a "greener" median voter are more likely to push towards voluntary cutbacks in emissions.

*We are grateful to Matthew Kahn and Gilbert Metcalf for insightful comments. We are responsible for any remaining errors. Send correspondences to Maximilian Auffhammer, Department of Agricultural and Resource Economics, 207 Giannini Hall, University of California, Berkeley, CA 94720-3310, USA, Phone: (510) 643-5472, Fax: (510) 643-8911, E-Mail: auffhammer@berkeley.edu.

1. Introduction

In the United States, anthropogenic emissions of the main greenhouse gas, carbon dioxide (CO_2) have doubled from 1960 to 2000. Over this entire time period, the US has been the largest emitter of this gas worldwide. In March 2001 the US withdrew from the Kyto protocol citing the excessive anticipated costs of the cutbacks as its main motivation. In 2005, overriding federal policy, several West and East coast states announced voluntary steps toward cutbacks, using measures targeting all or in some states specific sectors.

In standard static models of abatement choice, the marginal cost of abating the last unit currently produced enters the decision rule of whether and how much to abate. The vast majority of International Environmental Agreements require individual countries to cut back relative to a baseline emissions level in the past by some future target date. In the case of the Kyoto protocol, Annex 1 countries agreed to a 5.2% cutback from 1990 aggregate emission levels by the "first commitment period" (2008-2012).[1] Decisions to join/abate should therefore be made according to anticipated marginal abatement costs in 2008-2012, which are closely tied to the expected level of future emissions.

Using a recently made available panel data set on US state level emissions of carbon dioxide from 1960 - 2001, this paper tests the following hypotheses: When the goal is to forecast aggregate US CO_2 emissions out-of-sample, should we forecast individual states' emissions and then aggregate or should we simply forecast the aggregate directly? Are the states proposing voluntary cutbacks in emissions just agreeing to reductions which would occur anyway? Are "greener states" - meaning states with falling *per capita* emissions and/or a "greener" median voter - more likely to engage in these voluntary reductions?

Determining which level of aggregation is appropriate for forecasting the US aggregate is important for three reasons. First, providing better forecasts will result in better information to base national climate policy on, since better forecasts allow a more accurate estimate of the costs of reductions. Further, better forecasts of emissions are important as inputs into global circulation models, which provide estimates of future warming effects. Second, there is a literature in macroeconomics, which has suggested that forecasting the aggregate directly may be suboptimal

[1] The percent cutbacks ranged by country: The European Union (8%), US (7%), Japan (6%) and Russia (0%) agreed to cutbacks. Australia (8%) and Iceland (10%) were permitted increases.

when there is sufficient heterogeneity in the disaggregate series (Marcellino, Stock and Watson, 2003; Zellner and Chen, 2001). Giacomini and Granger (2004) show that if there is spatial dependence in the series, explicitly incorporating this information into the forecast model will result in improved out-of-sample performance. Confirming these findings for CO_2 would extend this literature to a series with a physically spatial dimension. Third, since total US emissions are the central series of interest, we forecast total emissions nationally and at the state level directly, instead of forecasting per capita emissions. The econometric literature on forecasting aggregate emissions from spatial aggregates has adopted the Environmental Kuznets curve as its preferred specification, which is the finding that *per capita* emissions increase in income until a threshold and then decrease (e.g. Schmalensee, Stoker and Judson (1998)). Forecasts of total emissions are constructed multiplying per capita series by population *and* aggregating across states to obtain the US forecast, which may lead to a amplifying estimation error from the individual series. We also only use information available at the time the forecast is made, instead of adopting a scenario analysis approach.

While changes in *e.g.* population, climate and income may help forecast CO_2 emissions out of sample, they ignore potential policy intervention by (groups of) states. In the second part of the paper we attempt to predict which states have proposed voluntary cutback measures. Explaining the emergence of voluntary efforts by individual states to reduce carbon emissions in 2005 has baffled many economists. Attempting to explain such behavior, given data prior to the revelation of such efforts, is important from two aspects. First, there is a literature in economics, which argues that any voluntary agreements just codify reductions, which would have been made by agents in the absence of such an agreement anyway (Murdoch and Sandler, 1997). By this reasoning, we should observe states with flat or dropping *aggregate* emissions proposing voluntary reduction efforts. Second, there is a large literature suggesting that the median voter elects officials who agrees to provide public goods most closely matched to the median voter's preferences. By that argument one should observe states, whose median voter has historically been more "green" as first movers in voluntary reduction efforts. We provide an empirical test, which shows that the latter type model is more likely to explain the set of states which have proposed voluntary cutbacks.

The remainder of the paper is structured as follows. The next section provides a description of the data we use. Section 3 discusses the forecasting models we use and provides estimation results. Section 4 provides the test and results for explaining which states have engaged in voluntary efforts.

Section 5 concludes.

2. Data

Overall CO_2 emissions are never directly measured, since the costs of monitoring such a large variety of mobile and stationary sources are prohibitive. The literature has therefore relied on emissions data sets based on the consumption of fossil fuels within the boundaries of countries, states or across sectors. Until recently state level data on carbon emissions were available for the 1990s only from the US Environmental Protection Agency (2003). The brevity of the individual state series did not allow a credible attempt at testing whether aggregating state level forecasts or forecasting the aggregate directly performed better out-of-sample. Recently two new sources of data have emerged. Aldy (2005a) constructed a panel of CO_2 emissions for the fifty US states from the Energy Information Administration energy consumption data. The nice feature about this data set is that the author accounted for production versus consumption of energy by netting out interstate electricity trade. The data set we will employ for our analysis is provided by Blasing, Broniak and Marland (2004).[2] This panel of carbon dioxide emissions is available for all 50 states and Washington DC from 1960 until 2001. We will use this data set, since it is publicly available and the group providing these data series is also responsible for the quasi-official data set on historical country level carbon dioxide emissions (Marland, Boden and Andres, 2004) employed by the vast majority of the literature (e.g. Schmalensee et al. (1998)). A visual inspection of the state level series shows the energy crises of the early 1970s and 1980 and to a slighter degree in 1990 as detectable in aggregate and per capita terms. The aggregate carbon series are assumed to be I(1) in logs, which is confirmed by sequential applications of the Elliott, Rothenberg and Stock (1993) test.[3]

For the multivariate class of forecasting models we will control for the main factors thought to be responsible for changes in CO_2 emissions - income, population, heating and cooling demand.

[2] For a detailed description of how the state level series were constructed, please consult http://cdiac.esd.ornl.gov/trends/emis_ mon/stateemis/emis_state.htm. The data we employ here do not account for cement manufacturing, gas flaring and releases from bunker fuels.

[3] Note that although this test arguably has improved power properties over the traditional Dickey Fuller type tests, due to the brevity of the series, we may fail to reject the null when we should not. Our approach, however, is consistent with Marcellino et al. (2003).

Table 1: Summary Statistics for Year 2001: Full Sample, Top (highest) and Bottom (lowest) 10 Per Capita Emitters

	All		Top 10		Bottom 10	
	mean	std	mean	std	mean	std
CO_2^{agg} (million metric tons of C)	30.81	30.44	42.81	52.03	23.81	31.48
$CO_2^{p.c.}$ (metric tons of C)	6.98	5.50	14.86	8.34	3.25	0.29
Income^{agg} (Billion 2001 US$)	173.83	205.15	115.90	184.19	263.01	364.35
Income$^{p.c.}$ ('000 US$)	29.15	4.36	26.60	2.87	32.96	5.25
Population (millions)	5.69	6.29	4.23	6.31	7.72	10.89
Heating Degree Days	5211.80	2310.63	6126.01	3186.65	5750.36	1405.55
Cooling Degree Days	1122.20	824.37	1047.73	921.47	508.93	251.15

Table 1 contains the summary statistics for the entire sample as well as the top ten highest and lowest emitters in per capita terms for the year 2001. We use state income in constant year 2001 US$ provided by the Bureau of Economic Anlysis (2005), which is the same series used by Millimet, List and Stengos (2003). Gross state product would be a preferred indicator, but official estimates only start in 1977. The population data employed in this paper are taken from Blasing et al. (2004), who obtained them from the state tables published by the US Census Bureau and the Energy Information Administration (2003). We further obtained state level heating and cooling degree days for each state from 1960 to 2000 directly from NOAA (2005). The 2001 values for heating cooling degree days were added from monthly cooling and heating degree days given by NOAA (Multiple Dates). We include all variables in log changes (growth rates), which is consistent with the level series being I(1) in logs. To account for temporary shocks not reflected in changes in income, we include three dummies for the energy crises (1973-75; 1979-81; 1990-91). We err on the side of including an additional year after the recovery of oil prices, as the immediate effects of the shock are still echoing.

A measure of the "green" median voter by state is not readily available. We therefore use the League of Conservation Voters Scorecard indicator to capture how concerned with environmental protection legislators elected by individual states are. Since the seventies the League of Conservation Voters (LCV) each year determines important environmental legislation in the US House of Representatives and the US Senate recording the legislators' voting behavior by state. The LCV Scorecard indicator gives a yearly percentage measure of the House and the Senate for each state on how many of the environmental legislations their elected representatives voted in favor of. We collected the LCV index for the house of representatives and the senate for the years 2001 through 2004.

3. Forecast Performance Comparison

The econometric literature on forecasting CO_2 has traditionally estimated a per capita relationship between emissions and income. The empirical finding (or lack thereof) of an inverse U contemporaneous relationship between per capita emissions and income has led authors to argue in favor (Schmalensee et al., 1998) or against (Holtz-Eakin and Selden, 1995) the existence of an Environmental Kuznets Curve relationship.[4] Estimating per capita relationships is also the standard approach in the energy demand literature, since the estimated per capita elasticities are very useful inputs for scenario analysis, when attempting to simulate the impact of different *e.g.* population and income growth scenarios on electricity demand. Our exercise here is to adopt a true out-of-sample forecasting approach applied to the aggregate realization of the series at time $t+1$ given information available today.

The series we are interested in forecasting is aggregate CO_2 emissions summed over the 50 US states.[5] The realization of the aggregate series in year t is denoted by C_t. By definition $C_t = \sum_{i=1}^{50} C_{i,t}$, where $C_{i,t}$ is the realization of total emissions for state i in year t. We assume that the log of the series is integrated of order one and therefore require that the model be specified in log differences (growth rates). The most general model we consider has the form:

$$c_{i,t} = \rho_i c_{i,t-1} + \psi_i \sum_{j=1}^{k} w_{ij} c_{j,t-1} + \beta_i \mathbf{z_{i,t-1}} + \alpha_\mathbf{i} + \varepsilon_\mathbf{i,t} \tag{1}$$

Lower case letters indicate growth rates. c_{it} is therefore the growth rate of state i's aggregate CO_2 emissions from year $t-1$ to year t. The α_i's are state specific constants, while $\mathbf{z_{i,t-1}}$ is a vector of lagged state specific control variables. Spatial dependence is represented by the $\sum_{j=1}^{k} w_{ij} c_{j,t-1}$ term. One of the main contributions of this section is to see whether adding information on spatial dependence of the c_{it} series improves out-of-sample forecasting performance. Finding evidence in

[4] We show in related work, even when the goal is to forecast per capita emissions, this static specification is outperformed by a large number of dynamic specifications which are not always non-linear in income.

[5] To be consistent with the next section of the paper, we remove Washington D.C. from the sample since it is not a state and does not have direct political representation in congress.

support of this hypothesis, would suggest that incorporating a more complete characterization of the spatial structure driving the factors causing emissions may lead to even more efficient forecasts. We base our notion of spatial dependence on the STAR estimator provided by Giacomini and Granger (2004), who show that if there is spatial dependence in the series being forecast, failure to account for this correlation across space will result in suboptimal forecasts. Carbon dioxide emissions are strongly correlated with industrial activity, transportation, heating and cooling demand. The non-random distribution of each of these factors across the United States as shown in the regional science and urban economics literature is a likely source of information for potentially improving state level and aggregate forecasts. The approach proposed by Giacomini and Granger (2004) assumes a known weight matrix. We construct a rook contiguity weight matrix, which is normalized to unity row sums.[6] The w_{ij} are the weights given to the previous year's growth rate of CO_2 emissions by its k neighboring states. For all states, with the exception of Hawaii and Alaska, these weights sum to one. The coefficient ψ_i, if significant, captures the notion of whether spatial dependence explains a statistically significant share of the variance.

As further controls, we include the growth rate of total state population, income, heating and cooling degree days and rerun all models controlling for the occurrence of the three main energy crises by including dummy variables for those years. In summary, the four methods we consider are:

1. A univariate autoregressive model with a first order lag (AR(1)) as well as selecting the optimal lag length via the Bayes Information Criterion (AR(*)).

2. A space time autoregressive model (Giacomini and Granger, 2004) with a first order time and spatial lag.

3. A first order autoregressive model controlling for growth rates in population, income, heating and cooling degree days as well as energy shocks.

4. A space time autoregressive model controlling for growth rates in population, income, heating and cooling degree days as well as energy shocks.

[6] We checked the results against a nearest neighbor weight matrix (three, four and five nearest neighbors). The rook contiguity matrix provided the best out-of-sample forecasts.

Table 2: Estimation Results: RMSFE Results

Model	(1)*	(2)**	(3)**	(4)*	(5)**	(6)**
AR(1)	1.00	0.97	0.91	1.00	0.97	0.92
AR(Optimal Lag Length)	0.98	0.92	n/a	0.98	0.93	n/a
AR(1) + Inc.	1.12	0.98	0.89	1.13	0.99	0.89
AR(1) + Pop.	1.00	0.96	0.90	1.00	0.97	0.91
AR(1) + HDD/CDD	1.08	0.90	0.79	1.07	0.91	0.80
AR(1) + Inc. + Pop.	1.07	1.01	0.90	1.08	1.01	0.91
AR(1) + HDD/CDD + Pop.	1.11	0.89	0.76	1.09	0.90	0.78
AR(1) + HDD/CDD + Pop.+ Inc.	1.22	0.87	0.73	1.21	0.89	0.75
Hawaii & Alsaka Included	No	No	No	Yes	Yes	Yes
Aggregation	National	States	States	National	States	States
Spatial Lags	No	No	Yes	No	No	Yes

* RMSFE are relative to AR(1) result in column one [four]. ** RMSFE are relative to same specification in first [fourth] column.

Our out-of-sample forecasting experiment is conducted as follows. For each forecasting model we produce a set of ten one step ahead forecasts for the years 1992 through 2001. For the aggregate series, we calculate the forecast error by subtracting the prediction from the actual realization. We then average the squared forecast errors over the ten periods for each model and report the root mean squared forecast error (RMSFE). Note, that this performance measure implies a quadratic loss function. For the state level series we produce one step ahead forecasts for each of the 50 states, sum the forecasts across state and calculate the forecast error of this aggregate. The RMSFE for each method is our measure of forecast performance.

Following Marcellino et al. (2003) we also conduct a series of tests judging the in-sample performance of the different forecasting models. First, we conduct a pooling test, which is a traditional F-Test of parameter equality across all states. If we would fail to reject the null of pooling, the disaggregate models are simply an inefficient over-parameterized equivalent of the aggregate model. We also conduct F-Tests to see whether adding extra variables to the univariate autoregressive specification explains a statistically significant share of the variance in the aggregate model. For both tests we use the full sample.

Table 2 presents the estimation results excluding and including two states generally considered to be outliers in this literature - Hawaii and Alaska. The results in terms of relative model performance are robust across the two samples. The same is true for absolute RMSFE performance.

[7] The RMSFE for each of the 8 models forecasting the aggregate emissions directly is reported in the first [fourth] column and expressed relative to the aggregate AR(1) model's RMSFE, which we consider as the benchmark. The second [fifth] and third [sixth] column report the RMSFE for forecasting the states individually and the performance of the STAR model respectively. These columns report the RMSFE relative to the same specification from column one [four], allowing for direct comparison of forecasting performance gains from disaggregating and including the spatial lags. Below we focus our discussion on the results for the sample including all states.

The table provides some very interesting insights. Overall forecasting state emissions directly and accounting for spatial dependence provides RMSFE performance gains relative to the same specification for the aggregate series by 7.78% - 25.41% depending on the model. Consistent with this finding we reject pooling of the coefficients for all models at the 1% level.

For the nationally aggregated series, when we include extra variables in the first order autoregressive model, we find that none of the added variables improve forecast performance over the simple AR(1) specification. Population is the only variable for which we reject exclusion at the 10% level using an F-test. In terms of forecasting performance it is equivalent to the AR(1) specification. All other variables have a higher RMSFE and high p-values for the exclusion F-test. Unsurprisingly, using an AR(1) does slightly worse than choosing the optimal lag length via an information criterion. These findings are consistent with Marcellino et al. (2003), who find that the aggregate AR(1) is not outperformed by any of the multivariate aggregate specifications using the national level of aggregation.

The models forecasting state level series, without controlling for spatial dependence, show improved forecasting performance when compared to the same specification using nationally aggregated data. The models with population and weather introduced separately register gains of 2.75% and 8.74%. When introduced jointly the gains are 9.61%. For the specification including income, population and weather the gains from disaggregation are 10.71%. In terms of overall forecasting performance, the AR(1) and optimal lag length AR models using state level data improve significantly in forecasting performance. Only three state level models with additional covariates outperform the aggregate AR(1) - the ones conditioning on population growth and changes in

[7] The RMSFE of the AR(1) model including AK and HI is 25.38. When excluding these states, the RMSFE is 25.98.

weather introduced separately and jointly. The overall gains from disaggregating relative to the aggregate AR(1) model from these three models are 2.84%, 2.56% and 1.03% respectively. It is important to note that gains from disaggregating for the optimal lag length AR model relative to the aggregate AR(1) are 8.24%, which is a quite dramatic performance gain.

The results from the STAR model show large performance gains across all models.[8] The gains in MSFE terms range between 5.40% and 16.46% relative to the disaggregated models without the spatial lags. It is noteworthy that all models outperform the aggregate AR(1). These performance gains are very large and consistent over a number of models we considered. We reran all models including the shocks for the energy crises and the performance of the models decreased slightly. The best performing model considered is the STAR model including Heating and Cooling Degree days and population. A close second is the model which only conditions on the weather variables. It is surprising that income adds so little predictive power to the forecasting model. Only in the disaggregated models including the spatial lags do models including income outperform the simple aggregate AR(1). We tested whether income works through longer lags, and the forecasting performance deteriorated with the number of lags added. This is possibly due to the fact that income is a very noisy measure with a less direct impact on CO_2 emissions than population and weather. Overall the performance gains for short run forecasts by explicitly including spatial information into the forecasting models appear to be sizeable.

4. Global Public Goods Provision by States?

Nine East Coast states[9] announced in 2005 that they will adopt voluntary cutbacks of CO_2 emissions from their power plants (DePalma, 2005). Three Western states (California, Oregon and Washington) have announced steps towards potentially more stringent reductions. These unilateral actions are curious from an economic perspective for three main reasons. First, a simple global public goods provision model would predict the emergence of such voluntary cutbacks by individual states as unlikely, due to free riding behavior by other states. From this perspective, the fact that

[8] Since the STAR estimator assumes a known weight matrix, searching over the optimal time lag structure may lead to selection issues if the weight matrix is not correctly specified. We ran this model and obtained RMSFE of 0.91.

[9] Connecticut, Delaware, Maine, Massachusetts, New Hampshire, New Jersey, New York, Rhode Island and Vermont.

the group of states spans both the largest and smallest states of the union (California and Rhode Island) is noteworthy. Second, individual states' decision makers must believe that overall benefits from their contribution to global cutbacks outweigh costs incurred in the present. The observed behavior would be consistent with the belief in a strong signalling effect of these voluntary actions. Using this argument Rhode Island, whose cutbacks relative to global emissions are very small, must be motivated by the precedent it sets for others to follow. In the case of California, one could argue that due to the size of its market for cars and other energy consuming appliances, it may force manufacturers to change their portfolio of products offered in the global marketplace to a less energy/carbon intensive one, serving as a first mover.[10] Third, it is notable that the states engaging in these voluntary reductions are all "blue states".

The small empirical environmental economics literature on voluntary provisions of pure public goods by states or countries has largely focused on production/emissions behavior of countries prior to international environmental agreements. Murdoch and Sandler (1997) use the Montreal Protocol on Substances That Deplete the Ozone Layer to show some empirical evidence that countries, which ratified the Montreal protocol engaged in emission reductions prior to these reductions becoming binding. They conclude that the agreement only codified reductions which would have also occurred in the absence of the Montreal Protocol. Auffhammer, Morzuch and Stranlund (2005) show some empirical evidence of strategic production behavior by ratifying nations prior to the Montreal Protocol, which resulted in a net increase of CFC production. A third factor, which has not been empirically examined in this context, is the fact that a "greener" median voter will elect officials, which will support/promote "greener" policies. In this section we intent to shed some light onto which factors predict the binary decision of whether to voluntarily engage in cutbacks of CO_2 emissions by individual states.

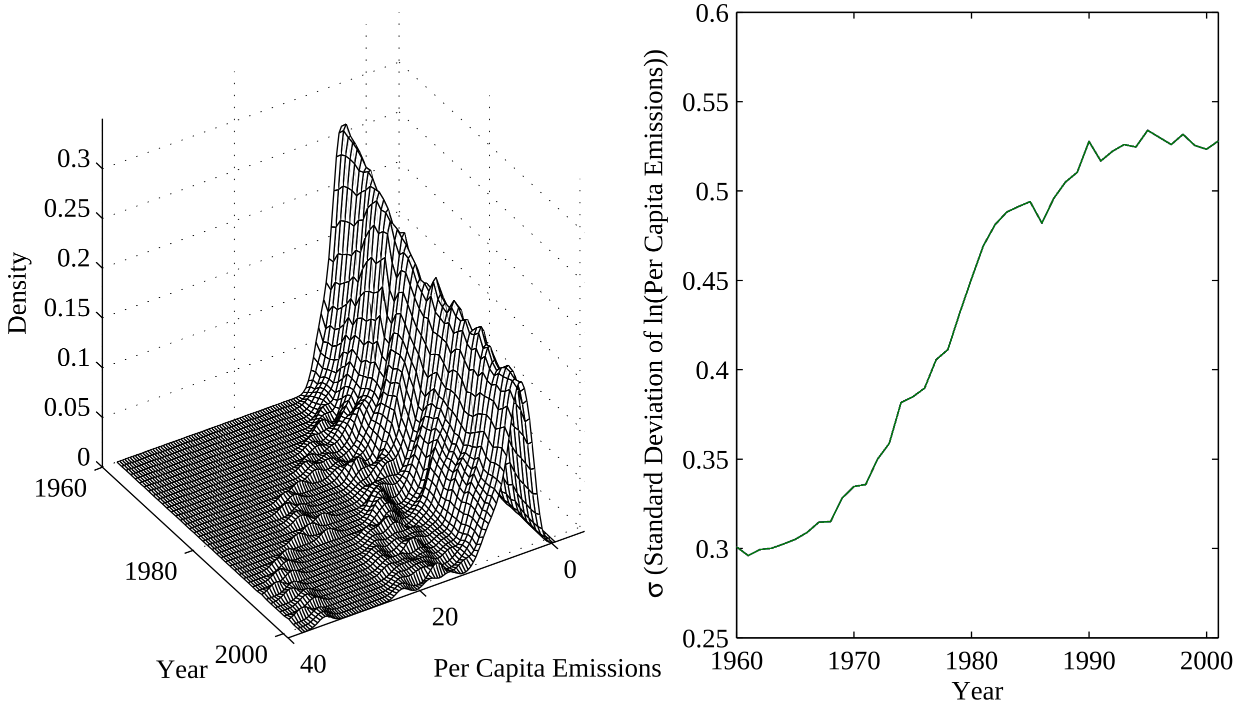
Aldy (2005a) using data for 48 US States shows that there is significant divergence in per capita emissions across US States. The existing heterogeneity in our aggregate and per capita emissions was shown in table 1 and is also visualized in figure 1. The left graph in figure 1 shows the evolution of the smoothed distribution of per capita CO_2 emissions across states.[11] The divergence of per capita emissions over the 42 years in our sample is apparent, showing strong evidence of

[10] For cars, California is the only state which can act as a first mover from a legal perspective.

[11] We used a normal kernel density smoother, with the bandwidth held constant at the optimum for 1960. Note that the distribution is not relative to annual overall mean, but in levels.

increasing heterogeneity across states. The right panel reproduces the σ-convergence plot by Aldy (2005b) using the data by Blasing et al. (2004). We confirm the same trend of σ-divergence.

Figure 1: Dynamic Distribution of State Level CO_2 emissions Per Capita



In order to test the hypotheses laid out in the introduction we use a multiple regression framework. We construct a binary variable, which is one for states which have announced steps towards voluntary reductions in emissions. If these voluntary efforts only codify reductions, which would happen in the absence of a voluntary policy as argued by Murdoch and Sandler (1997), we would expect states with dropping total emissions to promote voluntary cutbacks. We therefore construct a variable, ΔCO_2^{agg}, which is the mean % change in aggregate emissions for state j since 1973, which is the occurrence of the first energy crisis and therefore arguably the beginning of a new public awareness of energy consumption.[12] In order to estimate the impact of a"greener voter" on the probability of adoption of voluntary cutback efforts, we construct two variables. The first variable is $\Delta CO_2^{p.c.}$, which is the mean % change in per capita emissions for state i from 1973 until 2001. This variable is a commonly reported measure of gains in carbon efficiency of individual

[12]The results presented here are robust to including this variable as a mean over the entire sample.

states.[13] In order to better capture the "greenness" of the median voter, we use the mean of the League of Conservation Voters Scorecard indicators for the years 2001-2004.

Figure 2: Shades: Changes in Per Capita Emissions (73-01); Circles: House LCV Score (01-04)

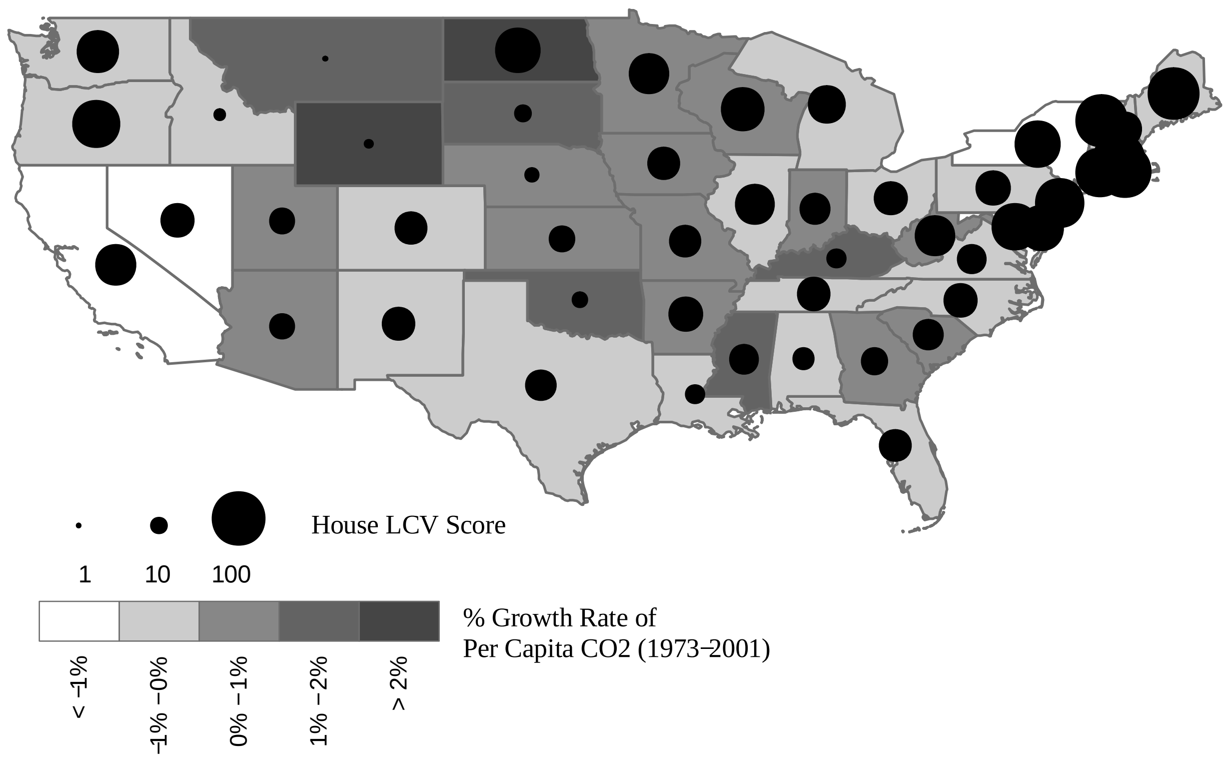


Figure 2 shows the distribution of drops in per capita emissions across states. States shaded white and light grey experienced drops in per capita carbon emissions since the first energy crisis. In addition to the states proposing voluntary cutbacks, Texas, the great lakes states, Nevada, Idaho and Florida have experienced noteworthy drops in per capita emissions. If we look at the distribution of the house LCV score across states, as indicated by the black circles, a noteworthy pattern emerges - all of the states proposing voluntary cutbacks are form the group with the highest LCV score (depicted is the score for the House of Representatives). While visual inspection tells part of the story, we will use a multiple regression framework to test whether the evidence is more consistent with the hypothesis posed by Murdoch and Sandler (1997) or with a median voter story. Since the dependent variable is binary, we run a logit model, explaining the decision to reduce

[13] On the contrary, a falling $\Delta CO_2^{p.c.}$ could also be due to a fast rising population even if carbon efficiency is falling or stable. One would need to assuming though, that the marginal consumer contributes lower carbon emissions.

Table 3: Logit Estimation Results: Probability of Voluntary Cutbacks

	(1)	(2)	(3)	(4)	(5)	(6)
LCV Senate Score	.055	.044	.040			
	(.016)***	(.016)***	(.015)***			
LCV House Score				.100	.096	.100
				(.028)***	(.030)***	(.035)***
CO_2 Per Capita Growth Rate (73-01)		-1.213	-1.124		-1.534	-1.577
		(.657)*	(.619)*		(.694)**	(.678)**
CO_2 Aggregate Growth Rate (73-01)			-.391			.184
			(.360)			(.450)
Const.	-4.360	-4.028	-3.456	-6.736	-7.211	-7.582
	(1.193)***	(1.116)***	(1.074)***	(1.751)***	(1.937)***	(2.331)***
Obs.	50	50	50	50	50	50
Log-Likelihood	-18.664	-16.812	-16.468	-12.998	-11.081	-11.034
Pseudo R^2	.323	.390	.402	.528	.598	.600

Note: Huber-Eicker-White Standard Errors are reported in brackets. Stars indicate statistical significance at the 1% (***), 5% (**) and 10% (*) level.

emissions as a function of ΔCO_2^{agg}, $\Delta CO_2^{p.c.}$ and the LCV score. Since the LCV score for the house and the senate are highly collinear across states, we include them separately. Table 3 shows the estimation results.

Estimation results indicate that a higher LCV score of a given state for both the US Senate as well as the House increases the probability of an individual state proposing voluntary cutbacks. The house score has a statistically larger impact compared to the senate score. This may be due to the fact that the large number of House seats, which are voted on at a finer spatial level of aggregation, are a better measure of a state's median voter. The per capita CO_2 growth rate has a negative impact on the probability of adoption. This indicates that states with a negative rate of growth of per capita CO_2 emissions since the first energy crisis are more likely to pass voluntary measures. Looking in the literature there are several reasons why per capita energy use and carbon emissions may have dropped. Some states have adopted more stringent regulation and voluntary programs to decrease energy use (e.g. California). The alternate explanation is that real energy prices have increased in spurts since 1973, resulting in substitution towards less energy intensive capital and appliances. Finally, the US economy has shifted towards a higher service/manufacturing ratio, which further drives down per capita energy use/carbon emissions. The final question to be asked is whether states with dropping aggregate emissions are more likely to engage in voluntary cutbacks. The table provides no supporting evidence of this hypothesis given our empirical model. The coefficients on the mean growth rate in aggregate state level emissions are not significantly different from zero and switch signs across models. The per capita and aggregate growth rates are highly collinear ($|\rho| = 0.71$). When we use the population growth rate, which is less strongly correlated with the per capita growth rate ($|\rho| = 0.19$) instead of the aggregate CO_2 growth rate the results are almost identical. When we include the aggregate growth rate on its own, it is statistically significant at the 10% level and negative, yet the coefficient is smaller. Overall we take this as suggestive evidence at best against the hypothesis that these states are committing to cutbacks which would have occurred anyway. Anecdotal evidence suggests that states have to engage in quite drastic measures to meet the voluntary cutbacks. The most prominent case of this is California's push for 90% reductions in CO_2 emissions by 2050.

5. Conclusions

This paper served two main purposes. First we used econometric forecasting models to construct one step ahead predictions of aggregate US CO_2 emissions. Estimation results suggest that forecasting individual state series results in modest predictive accuracy gains. Including additional conditioning variables in the aggregate model resulted in a deterioration of the model's ability to forecast. When forecasting the state series directly and then aggregating up, heating degree days and population proved to be the only useful controls in terms of improving predictive ability, yet both of these models perform very closely to an AR(1) specification at the state level.

We showed that large gains in predictive ability can be obtained from incorporating spatial information into the forecasting model. Specifically, using the STAR model proposed by Giacomini and Granger (2004) results in improvements in root mean square forecast error by between 7% to 26%. These results suggest that exploring the spatial dimension and spillover effects of carbon dioxide provide a promising step towards improving predictive ability of forecasting models.

The second part of the paper attempts to explain why twelve US states have moved towards voluntary cutbacks of CO_2 emissions - without any federal incentives to do so. We show empirical evidence consistent with a median voter type model. States with negative average per capita annual growth rates of emissions and more "green" representation in Congress are more likely to move towards voluntary cutbacks. The empirical results do not support a model, which predicts commitment to cutbacks which would occur in the absence of policy, as in Murdoch and Sandler (1997).

One interesting question one may ask, is which states, currently not moving towards voluntary cutbacks does the model predict to do so? Hawaii and Maryland have predicted probabilities close to one. But only time will tell how well our cross sectional model predicts out of sample!

References

Aldy, J. E.: 2005a, Divergence in per capita carbon dioxide emissions, *Harvard Department of Economics Working Paper* .

Aldy, J. E.: 2005b, An environmental kuznets curve analysis of u.s. state-level carbon dioxide emissions, *The Journal of Environment Development* **14**(1), 48–72.

Auffhammer, M., Morzuch, B. J. and Stranlund, J. K.: 2005, Production of chlorofluorocarbons in anticipation of the montreal protocol, *Environmental and Resource Economics* **30**(4), 377–391.

Blasing, T., Broniak, C. and Marland, G.: 2004, Estimates of annual fossil-fuel co2 emitted for each state in the u.s.a. and the district of columbia for each year from 1960 through 2000, *Trends: A Compendium of Data on Global Change* **Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, TN, U.S.A**.

Bureau of Economic Anlysis: 2005, State annual tables 2005., *Washington, DC: United States Department of Commerce* .

DePalma, A.: 2005, 9 states in plan to cut emissions by power plants, *The New York Times* p. A.1.

Elliott, G., Rothenberg, T. and Stock, J.: 1993, Efficient tests for an autoregressive unit root, *Econometrica* **64**(4), 813–836.

Energy Information Administration: 2003, State energy data report.

Giacomini, R. and Granger, Clive, W. J.: 2004, Aggregation of space-time processes, *Journal of Econometrics* **118**, 7–26.

Holtz-Eakin, D. and Selden, T. M.: 1995, Stoking the fires? co_2 emissions and economic growth, *Journal of Public Economics* **57**, 85–101.

Marcellino, M., Stock, J. H. and Watson, M. W.: 2003, Macroeconomic forecasting in the euro area: Country specific versus area-wide information, *European Economic Review* **47**(1), 1–18.

Marland, G., Boden, T. and Andres, R.: 2004, Global, regional, and national fossil-fuel co2 emissions, *Trends: A Compendium of Data on Global Change* **Carbon Dioxide Information Analysis Center, Oak Ridge National Laboratory, U.S. Department of Energy, Oak Ridge, TN, U.S.A**.

Millimet, D., List, J. and Stengos, T.: 2003, The environmental kuznets curve: Real progress or misspecified models?, *Review of Economics and Statistics* **85**(4), 1038–1047.

Murdoch, J. C. and Sandler, T.: 1997, The voluntary provision of a pure public good: The case of reduced cfc emissions and the montreal protocol, *Journal of Public Economics* **63**(3), 331–349.

NOAA: 2005, State heating and cooling degree days 1960 - 2000, *Private Communication to David Rich.* .

NOAA: Multiple Dates, Monthly state, regional, and national heating degree days, weighted by population 1999-2001, 2001-2003., *Historical Climatology Series 5-1; NOASS Natioanl Climatic Data Center.* .

Schmalensee, R., Stoker, T. M. and Judson, R. A.: 1998, World carbon dioxide emissions 1950 - 2050, *Review of Economics and Statistics* **80**(1), 15–27.

US Environmental Protection Agency: 2003, Inventory of us greenhouse gas emissions and sinks:1990 - 2001, **EPA 430-R-03-004**.

Zellner, A. and Chen, B.: 2001, Bayesian modeling of economies and data requirements, *Macroeconomic Dynamics* **5**(1), 673–700.