Have Greenhouse Gas Emissions from US Energy Production Peaked? State Level Evidence from Six Subsectors

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Abstract Analyses of the Environmental Kuznet's Curve (EKC) hypothesis have largely focused on economy level data with occasional analyses exploring sector level data. This paper exploits a new data set which contains sector level data on greenhouse gas emissions from the US energy sector as well as subsector data from six disjoint subsectors which together comprise the entire energy sector. The data contained in this data set is annual data at the state level from 1990 through 2011. By using differenced data we specify an econometrically sound EKC model and compare it against a model containing only a linear GDP per capita term. We find that by using a subsector level modelling approach, evidence for the EKC hypothesis is virtually nonexistent. Moreover, we find that aggregated subsector level estimates outperform sector level estimate on in-sample accuracy. These estimated models are then used to forecast emissions for the energy sector. We find evidence that US greenhouse gas emissions from energy production are at or near a peak.

Keywords Emissions · Energy · Environmental Kuznet's Curve · Panel Data · Subsector Analysis

JEL classification Q53, Q54, Q56, Q57

1 Introduction

The primary source of greenhouse gas (GHG) emissions from an economy is the energy production sector. Marrero (2010) determined that greater than 65% of the world's GHG emissions come from energy production

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with many OECD nations generating greater than 80% of their total GHG emissions from energy production. According to data from the WRI CAIT Climate Data Explorer (2014), the data set used for this paper, during the period from 1990 through 2011 the energy production sector accounted for more than 88% of total GHG emissions in the United States. Considering the contribution to total GHG emissions from the energy sector of the US economy, any analysis or forecast of GHG emissions in the United States must seriously consider the dynamics of GHG emissions due to energy production.

With new data from the WRI CAIT Climate Data Explorer data set, we explore for the first time the dynamics of six subsectors of the energy production sector of the US economy. By order of magnitude of GHG emissions, these six subsectors are: electric power, transportation, industrial, residential, commercial, and fugitive emissions. By not only studying the energy sector as a whole, but also by studying the behavior of its subsectors, we can improve our understanding of GHG emissions from energy production and thereby enhance forecasts of GHG emissions. By showing that this forecasting approach leads to greater accuracy when dividing data into training and testing periods, aggregated subsector forecasts are shown to be superior to sector level forecasts.

Since the quantity and composition of GHG emissions varies across sectors of the economy, and similarly across subsectors of the energy sector, no two subsectors of energy production should expect to benefit equally from any given emissions mitigation program. Moreover, technological advancement does not affect the energy production sector ubiquitously. By breaking the energy sector down into subsectors, we can increase our ability to estimate the effects of subsector specific tech-

nological advancements or emissions mitigation policies. As energy consumption habits are known to change with income, see, e.g., Caron and Fally (2018), energy production portfolios should vary across income levels and thus across states. For all of these reasons, finding an overall trend in GHG emissions from energy production will not be as accurate as finding an aggregated trend of the subsectors of energy production.

In order to study energy subsector GHG emissions, we use an econometrically sound variant of the Environmental Kuznet's Curve (EKC) approach. Under this approach, GHG emissions are differenced and these differences are estimated primarily as a function of GDP per capita. The EKC hypothesis states that there is an inverted "U" shape relationship between GHG emissions and GDP per capita. To test this hypothesis, models using the EKC approach include both GDP per capita and GDP per capita squared. The ecological consequences of this hypothesis are that, if true, GHG emissions are not a monotonically increasing function of production. That is to say, as production continues to increase, overall levels of emissions may actually decrease. Possible explanations for this behavior include the notion that the adaption of greener technologies, the switch to renewable sources of energy, and the implementation of other abatement strategies are all monotonically increasing functions of income.

The two overwhelming drivers of emissions from the energy production sector are electric power generation and transportation. Both electric power generation and transportation are areas which are experiencing rapid growth in the adaptation of greener technologies, the switch to renewable sources of energy, and in the growth of regulation which imposes, through various means, emissions limitations (Fox et al., 2017). However, the methods employed to achieve emissions reductions in these two subsectors are not identical, so our method of isolating these subsectors and studying and forecasting them independently of each other allows us to determine not only which factors influence emissions from energy production, but also how these factors influence emissions at the subsector level. Similarly, we can test not only whether the EKC hypothesis is likely for the energy production sector as a whole, but how valid the EKC hypothesis is for each of its subsectors. By studying the determinants of GHG emissions at the subsector level, better policy proposals and decisions regarding emissions and emissions abatement strategies can be made through this more in depth targeting of the energy production sector.

The remainder of this paper follows the following structure. After providing a review of the relevant literature, we describe our data set and the methodologies we employ to determine which factors influence emissions from the energy sector and its subsectors in the United States. At this point the results from the various regression models are presented and their results and implications for the EKC hypothesis are discussed. In particular, we show that when analyzing the subsectors of the energy production sector, no support for the EKC hypothesis exists. Moreover, we show through use of the Akaike Information Criterion (AIC) that a model specified to test for the EKC hypothesis is effectively not different from a model which includes only a linear term for GDP per capita. Once we have an understanding of these results, we describe our forecasting technique which comes from Selden and Song (1994) and forecast state level and total US GHG emissions for the energy production sector both independently and as an aggregate of the forecasts for each of its subsectors. To determine the validity of our aggregated forecasting technique, we show that aggregated fitted values from subsector models have greater in-sample accuracy in the energy sector level data by using a secondary data set from the EPA which includes national level GHG emissions data for an additional five years beyond what is offered by the WRI data set. Consequentially, we see that US GHG emissions from the energy production sector have likely peaked.

2 Literature Review

Selden and Song (1994) popularized the EKC hypothesis as a means for studying various GHG emissions. After testing the EKC hypothesis, which they found evidence for in the case of several greenhouse gases, they forecasted future emissions and found that GHG emissions were likely to taper off, though not decrease, over the next several decades. Since then, several papers have studied and tested the EKC hypothesis in various contexts.

Early support for the confirmation for the EKC hypothesis was given by List and Gallet (1999). From there, numerous case studies on various nations, US states, and global regions were performed. Friedl and Getzner (2003) studied the EKC hypothesis in Austria and found evidence for the standard EKC model with a cubic term for GDP per capita included. Similarly, Shittu et al. (2018) studied the EKC hypothesis in Malaysia, Kunnas and Myllyntaus (2007) studied the case of Finland, and Soytas and Sari (2009) did the same in Turkey. At the state level in the United States, Konan and Chan (2010) performed a case study on Hawai'i and Yang et al. (2009) performed a case study on California. On a much larger geographic scale, Zoundi (2017) studied the EKC hypothesis in Africa.

This analysis found ambiguous evidence, showing that in Africa CO_2 levels rise monotonically with rises in income.

However, not every study has provided the same level of support for the EKC hypothesis. Azomahou et al. (2006) found that the EKC hypothesis has more or less support in different countries and under different statistical approaches. The standard model for EKC hypothesis testing did exhibit evidence for the EKC hypothesis, but a non-parametric model found only limited evidence which varied widely by country. In the context of sulfur emissions specifically, Stern and Common (2001) found that there was support for the EKC hypothesis, but only for high income countries. The standard EKC model found monotonically increasing sulfur emissions when using a global data set.

There is much concern over the specification of EKC models due to the inclusions of multiple powers of GDP per capita. When a cubic term is included, it is possible to see an 'N' shaped model due to the effects of the cubic term. While this appears to lend some support to the EKC hypothesis over what could be considered a realistic income domain, Canas et al. (2003) pointed out that the 'N' shaped curve can perhaps be better thought of as an 'augmented' EKC. Hüttler et al. (1998) went further and asserted that the 'N' shaped curve supports not the EKC hypothesis, but a perverted variant in which emissions reduction with economic growth is merely a transitory phase that precedes a final phase in which further economic growth drives a rapid growth in emissions. Because of this, Canas et al. (2003) recommended that any inference of support for EKC models relying on significant effects from the cubic term should be taken cautiously.

Many more robust approaches for EKC models have been developed. Spatial models were first used as a tool for assessing the EKC hypothesis by Rupasingha et al. (2004). Extending the use of more sophisticated econometric approaches, Maddison (2006) studied a spatial variant of the EKC hypothesis for national emissions of SO_2 and NO_x and found evidence that national emissions are lowered by proximity to nations with high per capita income, contradicting the notion that nations must achieve increased environmental quality at the expense of their neighbors. Burnett et al. (2013a) also studied several spatial panel data models in the context of CO_2 emissions in the United States, and Ordás Criado (2008) performed a case study on Spain using non-parametric estimation techniques.

In addition to testing the EKC hypothesis with semi- and non-parametric and spatial econometrics models, recent emphasis has been placed on validating estimations and on the importance of the data itself. Chow and Li (2014) established a method using t-tests for validating conclusions supporting the EKC hypothesis using standard econometric approaches. However, Millimet et al. (2003) demonstrated that semi-parametric techniques tend to be superior to standard econometric approaches. As for the choice of data set on the part of the researcher, both Harbaugh et al. (2002) and Galeotti et al. (2006) showed that the data set chosen does not significantly impact any conclusions drawn from statistical analyses.

In lieu of testing the EKC hypothesis itself, the topic of convergence of per capita GHG emissions has also garnered recent attention in the literature. Aldy (2006) studied the convergence of per capita GHG emissions in OECD countries and found evidence supporting this idea. Criado and Grether (2011) found with non-parametric methods that convergence in per capita emissions existed only within groups of similar countries. Aldy (2007) found no evidence, in the context of the United States, for state-wise convergence in per capita emissions, while Burnett (2016) found a group of 26 states for which there is support for convergence in emissions. Relatedly, Tol et al. (2006) studied the EKC hypothesis for emissions intensities and Burnett et al. (2013b) found the economic growth drives not absolute emissions but emissions intensities.

Not all sectors of the economy are equally responsible for producing emissions. For this reason several papers have explored the EKC hypothesis for certain sectors of the economy. Using data from the industrial sector, Edelenbosch et al. (2017) forecasted decreasing energy intensities for this sector in non-OECD countries following a brief increase in industrial energy demand in the short term. Suri and Chapman (1998) first studied the EKC hypothesis in the context of energy consumption. Expanding on their results, Soytas et al. (2007) investigated energy consumption in the United States and found that increases in energy use, not increases in income, cause carbon emissions in the United States by using a Granger causality test. This result is noteworthy because it implies that economic growth alone is not a solution for long term emissions reductions.

Furthering these sector level analyses, Bruvoll and Medin (2003) looked at potential economic factors driving air pollution and found that changes in the relative size of different sectors of the economy helps drive changes in emissions. Mazzanti et al. (2008) used data on value added and capital stock per employee as covariates and found that the inclusion of these measures of labor productivity led to mixed support at the sector level for the EKC hypothesis in the case of Italy.

In the United States, another interesting way to subdivide emissions is at the state level. Aldy (2005)

studied per capita emissions at the state level, finding that the estimated EKC varied by state. Using a spatial autoregressive model, Burnett and Bergstrom (2010) found further evidence for the EKC hypothesis in the United States. Auffhammer and Steinhauser (2012) found that, while standard EKC models did well with in sample accuracy (R^2, Akaike Information Criterion, Schwartz Information Criterion, and others), they were not the top performing models for out of sample testing. Combining the state level and sector specific analyses, Zhou and Gurney (2011) used a spatial econometric model to study sector specific emissions and the state and county level in the United States. Using surface temperature data, they found that emissions due to space cooling in warmer climates should more than offset any future emissions reductions due to reduced needs for space heating. A study by Apergis et al. (2017) found limited evidence for the EKC hypothesis at the state level (10 of 48 states fit the hypothesis) using a standard EKC model without a cubic term.

Using a similar basis, namely province level EKC testing on province level data from China, Auffhammer and Carson (2008) forecasted aggregate Chinese emissions. Of particular interest in this paper was the response by the forecasted Chinese emissions to the Kyoto Protocol. More generally, the theme of increased emissions mitigation techniques, ranging from legislation to greener technologies to socioeconomic inequality and beyond, to combat global climate change and increased air pollution have also been studied in the context of the EKC hypothesis. Magnani (2000) studied how income inequality affects investment into emissions mitigation R&D and found that income inequality leads to a gap between the willingness to pay of a country and its ability to pay.

The negative externalities associated with GHG emissions and how they will impact the economy are currently attracting much attention from interdisciplinary researchers. Fankhauser and Tol (2005) studied the effects of climate change on capital accumulation, finding that forward looking agents are likely to change their savings behavior which will lead to reduced economic growth. A growth model with endogenous emissions reduction was created by Criado et al. (2011), and by using data from European nations they were able to validate this theoretical model. Simulations of the impact of automation on emissions at the household level were performed by Ringel et al. (2019), demonstrating evidence that automation of lighting, heating, and cooling in a household can help reduce emissions. Al-Mulali et al. (2015) studied contributing factors to air pollution in Vietnam and Yates and Strzepek (1998) found that climate change had a minimal impact on agricul-

tural production in Egypt. Beyond agricultural production, the negative externalities due to emissions are vast and include depletion of the ozone layer, primarily due to N2O emissions (Ravishankara et al., 2009). Additionally, impacts on human health due to emissions, including increased risks of various chronic respiratory diseases and cancers (Kampa and Castanas, 2008), are also concerns which emissions mitigation policies attempt to address. The economic impact of increased health risks due to emissions are well documented (West et al., 2013).

We conclude the literature review section of this paper by acknowledging several well written survey papers on the EKC hypothesis which the reader may find helpful, including (Dinda, 2004), (Gill et al., 2018), (Stern, 2004), and (Stern, 2017).

3 Data

The basis for our data set is from the WRI CAIT Climate Data Explorer (2014). This data set is the only data set known to the author which includes GHG emissions data not only for the energy production sector, but for its comprising subsectors (electric power generation, transportation, industrial, residential, commercial, and fugitive emissions). This data considers total GHG emissions in Mt CO_2 equivalent rather than by Mt of individual chemical species. This data is at the state level, includes estimates of GDP per capita and population, and covers the time period from 1990 to 2011. While 22 years is a relatively short period of time, the novelty and level of specification of this data set allows us to be the first to analyze GHG emissions at the state level for subsectors of the US energy production sector.

The socioeconomic data used in this study includes GDP per capita and population density. The WRI data set included GDP per capita and population. To derive population density, the given population of each state was divided the area of the state in square kilometers. To address the various state level portfolios of energy sources (i.e., clean versus fossil fuels), we use data on this blend from the Administration (2019). Because climate change is a significant concern in forecasting future energy consumption and emissions, we include data on heating degree days and cooling degree days from United States National Climate Data Center (2019). Heating degree days are defined as those days on which the average temperature is below 65 degrees and cooling degree days are defined as those days on which the average temperature is above 65 degrees. We differentiate between these because they often use different fuel sources.

The data for the subsectors exhibit several important quantitative and qualitative properties. First, the sum of GHG emissions over all subsectors in a fixed year and state are equal to the total GHG emissions from the energy sector in that same state and year. Qualitatively, there are two primary drivers of the energy production sector (electric power generation and transportation), and the three largest subsectors account for nearly 90% of GHG emissions from US energy production. The average contribution of each subsector to total GHG emissions from energy production over all states and years in the data set is summarized in the table below.

Table 1:
Contribution of each subsector to GHG emissions from energy production

Subsector	Contribution
Electric Power	36.23%
Transportation	32.16%
Industrial	18.60%
Residential	6.18%
Commercial	3.90%
Fugitive Emissions	2.91%

In order to validate the forecasts using the WRI data, we use national level data from the United States Environmental Protection Agency (2019) which extends through 2017.

4 Methodologies

This paper has two primary goals: to test the EKC hypothesis for GHG emissions from the US energy production sector and its subsectors, and to forecast GHG emissions from US energy production using these results. In this section we detail the regression models used to test the EKC hypothesis on the data set.

As detailed in the literature review section of this paper, several regression techniques, including fixed effects models, random effects models, autoregressive models, semi- and non-parametric techniques, and spatial regression models have been used on various data sets to test the EKC hypothesis. In this paper we use two different models applied to each of the six subsectors of the energy production sector as well as the energy production sector itself. These models are both variants of autoregressive models with covariates, with one model testing the EKC hypothesis (i.e., it includes GDP^2) and one which does not include the GDP^2 term to serve

as an econometrically sound comparison for the EKC model. Eventually, the estimated coefficients from both models will be used in our forecasts.

In order to test the EKC hypothesis for GHG emissions in a statistically sound manner, we measure the change in emissions at each time step. By measuring the change in emissions rather than directly measuring the volume of emissions, we avoid many econometric flaws associated with EKC models (Burnett et al., 2013a). The EKC model takes on the following specification in which the variable $\Delta_{s,t}$ represents total GHG emissions from state s in year t, $y_{s,t}$ represents GDP per capita in state s in year t, $p_{s,t}$ represents the population density of state s in year t, $h_{s,t}$ represents the number of heating degree days in state s in year t, and $c_{s,t}$ represents the number of cooling degree days in state s in year t.

$$\Delta_{s,t} = \beta_1 y_{s,t} + \beta_2 y_{s,t}^2 + \beta_4 p_{s,t} + \beta_5 h_{s,t} + \beta_6 c_{s,t} + \epsilon_{i,t} \tag{1}$$

In the second model which serves as a comparison for the EKC model, we simply remove the $y_{s,t}^2$ term and its coefficient from the first model.

After estimating each model, the estimated coefficients are used to find the point at which GHG emissions peak according to the EKC hypothesis. This is done by using the parameters β_1 and β_2 by checking that $\beta_1 > 0$ and $\beta_2 < 0$. If so, the estimated peak, or turning point as it is often called, is given by $\frac{-\beta_1}{2\beta_2}$. In instances in which the coefficients reject the EKC hypothesis, i.e., they do not fit the above form and thus monotonically increase, we denote the estimated turning point by —.

The forecasts performed using this data are validated with national level data from the EPA. To ensure that we have a reliable basis for comparing the performance of the forecasts using each model, we transform the EPA data to fit the national level WRI GHG emissions data using a standard univariate OLS regression approach. By using GHG emissions data from 2012 through 2017, this allows us to use mean squared error (MSE) as a metric for assessing which forecasting approach is superior.

5 Results

Since we are analyzing results from not only the energy sector as whole, but for six subsectors of this sector, we break this section down into seven subsections, one for the energy production sector and one for each of its six subsectors. In each subsection we will present the estimates from the regression models, provide the estimated turning point ($\frac{-\beta_1}{2\beta_2}$) representing an estimated

peak emissions level, and discuss whether the results fit the EKC hypothesis.

Overall we do not find evidence for the EKC hypothesis for the energy sector, even when we restrict our analysis to the subsector level. This is evidence that any claims supporting the EKC are quite possibly spurious due to misspecified econometric models. Moreover, we find that the linear GDP model outperforms the EKC model in terms of forecast accuracy.

The tables for the results discussed in this section can be found in Appendix A. In those tables, the symbol * will denote that a variable is significant at the 10% level, ** will denote significance at the 5% level, and *** will denote significance at the 1% level.

We begin by examining the US energy production sector as a whole. The data set used for this study broke down the energy production sector into six disjoint subsectors: electric power, transportation, industrial, residential, commercial, and fugitive emissions. An initial survey of the estimates from the regression models, presented in Tables 3 and 4 in Appendix A, immediately dissuades us from making any conclusions in support of the EKC hypothesis. In none of the models using the EKC specification was the coefficient β_1 positive. This means that the EKC hypothesis was not supported at either the level of the energy production sector or for any of its subsectors. When comparing this against the linear GDP model by using the Akaike Information Criterion (AIC), we see no substantial difference between the two approaches. Considering that the coefficient β_1 behaves the sames under both model specifications and that the GDP squared term in the EKC model was only statistically significant in one instance (for the energy sector as a whole), the AIC statistics suggest that the two models are effectively the same, further eroding support for the EKC hypothesis.

Moving beyond the income terms, we see that the significant factors were heating degree days and cooling degree days. An increase in the number of heating or cooling degree days corresponds to an increase in emissions; however, cooling degree days were responsible for roughly triple the increase in emissions, suggesting that, at least in the United States, temperature increases could have a slightly net negative effect on GHG emissions.

Interestingly enough, these results suggest that GHG emissions from the energy production sector have likely peaked.

Moving on to the subsector level analyses, we see a nearly identical story. Heating degree days and cooling degree days are the most significant covariates included in this study, with both of these variables being statistically significant in the majority of models.

We do take the time to mention that some subsectors could benefit from perhaps a more targeted set of covariates. For example, transportation is relatively elastic in how it is consumed when compared to the other subsectors. For this reason, transportation is a common target of emissions mitigation policies, legislation, and technologies (Fox et al., 2017). Furthermore, emissions from transportation often occur in heavily populated areas. These emissions contribute directly to numerous negative health consequences (Kagawa, 2002), further incentivizing reductions in emissions from this subsector. Alternatively, results from fugitive emissions are due to faulty equipment, faulty processes, and corporate corruption, among other distinct factors. For this reason, results for fugitive emissions indicate that the factors which contribute to changes in emissions in other subsectors are not as impactful on fugitive emissions.

6 Forecasting GHG Emissions

Forecasts are a valuable tool for policy making, in part because they all for us to attempt to answer the question of whether or not emissions have likely peaked. Using the results from our econometric models, we forecast GHG emissions from the US energy production sector using the forecasting method used by Selden and Song (1994). We then complement these forecasts using aggregated subsector emissions forecasts following the same methodology. This dual forecasting approach allows us to achieve several novel results. First, it allows for us to forecast GHG emissions at the subsector level. Additionally, this allows for state level forecasts of emissions at the subsector level. But most importantly, we can compare aggregated forecasted subsector emissions against forecasted emissions from the energy sector as a whole. By doing so, we can potentially improve upon forecasts of emissions from the energy production sector.

In order to justify this forecasting approach, we first present a comparison of the in-sample accuracy of the models for the energy sector as a whole versus the accuracy of aggregated subsector models. We find that, in accordance with the 'sum of the parts is more than the whole' approach espoused by Ferreira and Santa-Clara (2011), the aggregated subsector models are more accurate than the energy sector models. The following table contains the comparisons between the Adjusted R^2 values for the independent energy sector models and the aggregated energy subsector models within the energy sector data.

Since the EKC hypothesis asserts that GHG emissions are a function of economic growth, we can forecast

Table 2: Comparison of MSE Values

Model	Mean Squared Error (MSE)	
	Aggregate	Independent
EKC	1.47e5	1.93e5
Linear	6.07e3	3.07e4

GHG emissions using the estimated parameters from our regression models and forecasted economic growth. Because economic growth in the United States is relatively consistent, we can forecast GDP per capita on a state by state basis with the following model specified by Selden and Song (1994) in which $y_{i,t}$ represents GDP per capita in state s in year t, and $\theta_{s,t}$ denotes the error term.

$$\ln\left(\frac{y_{s,t}}{y_{s,t-1}}\right) = \gamma_0 + \gamma_1 \ln(y_{s,t-1}) + \gamma_2 \ln(y_{s,t-1}^2) + \theta_{s,t} \quad (2)$$

Because we used a series of covariates in our regression models, and because these covariates can be easily forecasted with reasonable accuracy, we include forecasts for each covariate in our forecasts using a linear trend on a state by state basis. We then use our forecasted GDP per capita and forecasted covariates along with the estimated parameters from each of our models to create a raw forecast of emissions for each model and (sub)sector combination over the period from 2012 through 2017, the time period for which we have additional national level GHG emissions data from the EPA.

These raw emissions are then transformed using a Tobit functional form. This approach flattens forecasts, creating more gradual increases and decreases. Selden and Song (1994) preferred this method for asymptotic properties compared to the standard EKC and because it does not affect the turning points estimated by the EKC model. The Tobit transformation used here is given by the following equation in which $\hat{m}_{s,t}$ denotes the Tobit transformed forecasted emissions for state s in year t, $m_{s,t}$ denotes the raw forecasted emissions for state s in year t, Φ denotes the standard normal cumulative distribution function, ϕ denotes the standard normal probability distribution function, and σ denotes the standard deviation of the error terms in the original regression models from which the forecasts are based.

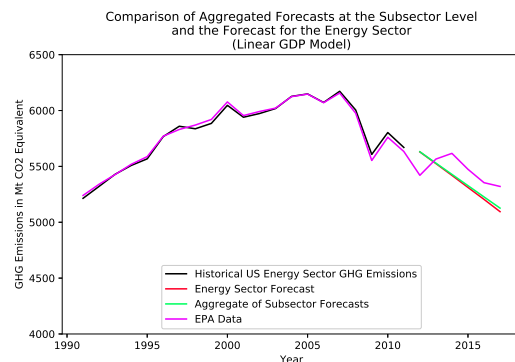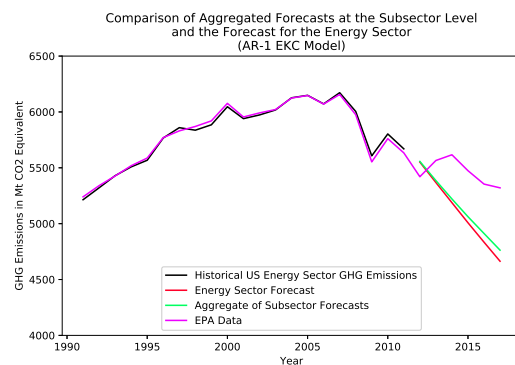$$\hat{m}_{s,t} = \Phi\left(\frac{m_{s,t}}{\sigma}\right) * m_{s,t} + \sigma * \phi(m_{s,t}) \quad (3)$$

Once the Tobit transformations are complete, we aggregate the state level forecasts for each model into a single national level forecast of GHG emissions.

The forecasted models are presented below and are grouped by model. For legibility purposes, the forecasts are separated into two plots. Before discussing the results, we mention that both models predict decreasing GHG emissions going forward,

Throughout all forecasts we see that the aggregated forecasts, which we just demonstrated to be more accurate within the data set, universally predict a slower decrease in future emissions than the forecasts using energy sector level data. This indicates that forecasts based on the EKC are relatively inaccurate; in this case we see that forecasts based on the standard EKC consistently forecast below aggregate forecast levels. Given that the aggregated subsector level models outperform the energy sector level models for in-sample accuracy, we conclude that the 'sum of the part is greater than the whole' concept applies to emissions estimation and forecasting at the sector and subsector level.

Additionally, we see that, even with most of the models supporting the EKC hypothesis, volumetric emissions are forecasted to increase in roughly half of the models, even when aggregating subsector level forecasts. These forecasting results are consistent with those from Selden and Song (1994), indicating that even if economic growth eventually leads to reduced GHG emissions, we should not rely solely on economic growth as a means to reduce existing levels of greenhouse gases in a meaningful time frame.

Comparison of Aggregated Forecasts at the Subsector Level and the Forecast for the Energy Sector (AR-1 EKC Model)

Comparison of Aggregated Forecasts at the Subsector Level and the Forecast for the Energy Sector (Linear GDP Model)

7 Conclusion

In this paper we tested the EKC hypothesis for GHG emissions from the US energy production sector and its subsectors using an econometrically rigorous variant of the autoregressive EKC regression model which models GHG emissions as a function of economic growth. We found no evidence for the EKC hypothesis at either the energy production sector level or at the subsector level. The behavior of the linear GDP term was the same (negative coefficients) for a linear GDP model, further supporting that the EKC hypothesis is not the best approach to modelling GHG emissions.

After testing the EKC hypothesis for the energy production sector of the US economy and its six subsectors, we forecasted future emissions for the energy production sector both independently and as the aggregate of forecasts of its subsectors. We found that the aggregated forecasts were sightly higher than the independent forecasts, demonstrating a lessened decrease in emissions during the forecast. This result was validated with in-sample testing of the accuracy of these two approaches. Both models suggest that US GHG emissions due to energy production have peaked.

To extend this research, we suggest that this approach of subsector level emissions based analysis and forecasting be applied elsewhere, beyond the United States. In-sample accuracy testing may not necessarily offer the same results (though it should), so any subsector level forecasting should pay special attention to how it is validated.

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A Regression Tables

Table 3: Estimation Results for the EKC Model

Variable	Energy Sector	Electric Power Subsector	Transportation Subsector	Industrial Subsector	Residential Subsector	Commercial Subsector	Fugitive Emissions
GDP	-0.0001***	-6.827e-5**	-9.52e-6	-2.766e-5	-1.849e-5**	-6.701e-6	-9.557e-6
	(4.79e-5)	(2.74e-5)	(1.72e-5)	(2.12e-5)	(7.29e-6)	(4.61e-6)	(6.84e-6)
GDP^2	8.138e-10***	4.118e-10	-3.795e-11	1.685e-10	1.152e-10	4.212e-11	1.141e-10
	(4.64e-10)	(2.65e-10)	(1.67e-10)	(2.05e-10)	(7.05e-11)	(4.46e-11)	(6.62e-11)
Population Density	0.0016	0.0006	0.0010	-1.058e-5	0.0003	9.33e-5	-0.0005
	(0.003)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Energy Blend	0.1978	0.3004	0.0242	-0.0833	-0.1215	-0.0596	0.1377
	(0.734)	(0.419)	(0.264)	(0.324)	(0.112)	(0.071)	(0.105)
Heating Days	0.0006***	0.0002***	6.828e-5	0.0001	9.469e-5***	3.754e-5**	1.393e-5
	(0.000)	(9.43e-5)	(5.93e-5)	(7.29e-5)	(2.51e-5)	(1.59e-5)	(2.36e-5)
Cooling Days	0.0019***	0.0010***	0.0004**	0.0002	0.0002***	7.015e-5	3.103e-5
	(0.000)	(0.000)	(0.000)	(0.000)	(6.48e-5)	(4.1e-5)	(6.08e-5)
Adjusted R^2	0.032	0.035	0.022	0.003	0.013	0.001	0.002
AIC	6335	5206	4272	4688	2537	1615	2409
Turning Point	—	—	—	—	—	—	—

Table 4: Estimation Results for the Linear GDP Model

Variable	Energy Sector	Electric Power Subsector	Transportation Subsector	Industrial Subsector	Residential Subsector	Commercial Subsector	Fugitive Emissions
GDP	-5.949e-5***	-2.743e-5***	-1.328e-5***	-1.094e-5*	-7.073e-6***	-2.523e-6*	1.763e-6
	(1.35e-5)	(7.74e-5)	(4.86e-6)	(5.98e-6)	(2.06e-6)	(1.3e-6)	(1.93e-6)
Population Density	0.0011	0.0004	0.0011	-0.0001	0.0002	6.929e-5	-0.0005
	(0.003)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Energy Blend	-0.0054	0.1976	0.0336	-0.1254	-0.1503	-0.0701	0.1092
	(0.726)	(0.414)	(0.260)	(0.320)	(0.110)	(0.000)	(0.104)
Heating Days	0.0004***	0.0001**	7.766e-5	8.48e-5*	6.623e-5***	2.713e-5**	-1.428e-5
	(0.000)	(6.79e-5)	(4.27e-5)	(5.25e-5)	(1.81e-5)	(1.14e-5)	(1.7e-5)
Cooling Days	0.0014***	0.0008***	0.0004***	9.596e-5	0.0001***	4.268e-5	-4.34e-5
	(0.000)	(0.000)	(0.000)	(0.000)	(4.56e-5)	(2.89e-5)	(4.29e-5)
Adjusted R^2	0.030	0.034	0.023	0.004	0.012	0.001	0.000
AIC	6336	5207	4270	4686	2537	1614	2410

B Code and Data Source Availability

The python script and csv files containing data from
WRI CAIT Climate Data Explorer (2014) are available
online at:

    https://github.com/cat-astrophic/energy_subsector_emissions

Please cite the data source if using the data used in
this paper, but feel free to use, edit, and redistribute
the script state_level_stats.py freely!