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Drivers of greenhouse gas emissions in the United States: revisiting STIRPAT model

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Abstract

The challenge of reducing emissions of greenhouse gases (GHG) has stimulated great attention among policymakers and scholars in recent past, and a number of STIRPAT (Stochastic Impacts by Regression on Population, Affluence, and Technology) studies on carbon emissions have been conducted. This paper contributes to that literature by: (i) studying per capita GHG emissions in the United States (US) adopting STIRPAT modeling framework; (ii) employing new explanatory factors like cattle population density, political willingness to address environmental problems, and educational attainment; and (iii) investigating whether emissions elasticities of various factors vary within the US or not. State-level panel data over the period 1990–2014 are used, and partitioning of the sample is done with respect to two controlling factors: an indicator of political support to environmentalism and educational attainment. Results of heterogeneous slope parameters panel data models indicate that cattle density and affluence are major drivers of per capita GHG emissions in the continental US. We find strong evidence of heterogeneity in emissions elasticities across partitioned samples. Our grouping analysis suggests that in a diverse country like US, policymakers should not focus on the average relationships dictated by a single STIRPAT equation, but should account for regional differences if they want accuracy and higher effectiveness in climate policymaking.

Keywords Augmented mean group estimator · Climate change · Greenhouse gases · Livestock · Renewable energy · Population aging

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1 Introduction

About 16% of 2011 global carbon dioxide (CO_2) emissions originate from the United States (US)—world's largest historic greenhouse gases (GHG) emitter (Boden et al. 2015). However, the US did not participate positively in global climate negotiations and refused to set concrete GHG reduction targets until the Obama administration came to power. For a long time, there was no federal climate policy in place, but few makeshift initiatives at state level with uneven intensity were noticed. Finally in April 2016, the US ratified the 2015 Paris Climate Accord to cut down their GHG emissions but withdrew from the pact in June 2017 under a new political leadership. Interestingly, the governors of several states have refused to abandon the objectives of the Paris Agreement despite federal withdrawal from it. They have formed the US Climate Alliance to uphold the Paris Agreement (Gilmore and St. Clair 2017), and as of February 2018 this coalition includes 16 states contributing about 25.5% of US CO_2 emissions in 2014 and covering around 40.6% of US population in 2016. Public opinion is also divided on President Trump's decision of US withdrawal from the Paris Agreement. The Washington Post/ABC News has conducted a poll on June 2–4, 2017 to find that 59% of the American adults have opposed this decision.

Policy measures addressing GHG emissions in the US are diverse owing to differences in beliefs and concerns regarding climate change. Recently, Dietz et al. (2015) find that states with more environment-friendly policies have cut their GHG emissions despite rising population and affluence, while other states which are not pro-environmental have experienced rising GHG emissions. This dichotomy is evident from Fig. 1 which illustrates the percentage change in per capita GHG emissions over 25 years (1990–2014). Ten states[1] out of the 48 contiguous states witness positive growth in their per capita emissions. Moreover, Fig. 2 depicting state-wise per capita GHG emissions in 2014 also corroborates the fact that states which have experienced positive growth in their per capita GHG emissions are also having higher per capita GHG emissions in 2014 as compared to their counterparts. Meanwhile, the nation as a whole experiences a decline in per capita emissions during 1990–2014. Evidently, with a divided house, the US has reached a crossroads regarding GHG abatement. In this context, a thorough econometric analysis along the line of 'Stochastic Impacts by Regression on Population, Affluence, and Technology' (STIRPAT) modeling framework[2] (Dietz and Rosa 1997) cannot only help in recognizing the main drivers of GHG emissions in the US, but also helps in educated policymaking.

Our research is also motivated by a set of facts that arise from the growing STIRPAT literature exploring the impact of various socioeconomic and demographic variables on CO_2 emissions. Although there exists a plethora of STIRPAT studies on CO_2 emissions in various parts of the globe, studies on GHG emissions are rare. A notable exception is the work by Marcotullio et al. (2013) who have used STIRPAT modeling framework to analyze global urban GHG emissions. Methane is the second largest contributor to GHG pool and has 21 times higher global warming potential than CO_2, but has received little

[1] List of ten states: Oklahoma, Rhode Island, Illinois, Arkansas, Missouri, South Dakota, Mississippi, Iowa, Nebraska, and North Dakota.

[2] Ehrlich and Holdren (1971) introduced a mathematical identity I ≡ PAT (I: environmental impact; P: population; A: affluence; T: technology) which has been used as a modeling framework for analyzing the main drivers of anthropogenic environmental impacts. In 1990s, scholars reformulated IPAT model to its stochastic cousin named STIRPAT which allows both hypothesis testing as well as relaxes the implicit assumption of proportionality to conduct empirical research.

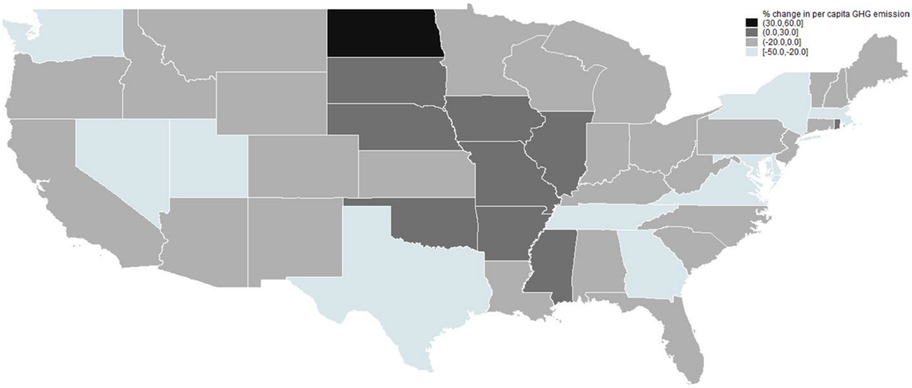

Fig. 1 Change in state-level per capita GHG emissions (1990–2014)

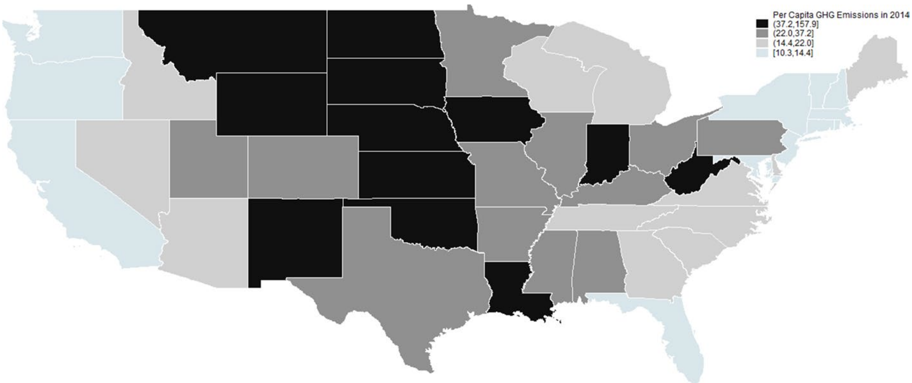

Fig. 2 State-level per capita GHG emissions in 2014

attention in the STIRPAT literature. Similarly, livestock farming—one of the key anthropogenic factors causing GHG emissions—has been overlooked so far. Ruminant production is the largest source of methane (Ripple et al. 2014). The Food and Agriculture Organization (FAO) appraises that livestock sector is responsible for 14.5% of world's anthropogenic GHG emissions (Gerber et al. 2013). Besides the past contribution of livestock sector in GHG emissions, most crucial aspect to analyze would be the impact of its expansion in nearby future. Due to rising population coupled with increasing affluence, demand for livestock products is expected to rise. According to an estimate, till 2050 meat and milk demand would increase by 73% and 58%, respectively, from their consumption levels in 2010 (FAO 2011). Thus, the contribution of livestock sector to GHG emissions remains crucial in coming future. Except for a couple of studies (e.g., York et al. 2003a; Jorgenson 2006; Squalli 2017), scholars neglected methane emissions in STIRPAT analysis.

Next, we discuss some knowledge gaps in the existing US-specific GHG-based STIRPAT and related literature. First, although there exists few STIRPAT studies on the US CO_2

emissions but only Squalli (2017) emphasizes on GHG emissions as a whole. The US is responsible for 30–60% of the growth in global anthropogenic methane emissions over the period 2002–2014, because of a 30% rise in methane emissions across the country (Turner et al. 2016), and it has the fourth largest cattle inventory of the world (FAO 2013). According to recent estimates, livestock production accounts for only 4.2% of total GHG emissions, but livestock farms contribute about 31% of total anthropogenic methane emissions in the country (USEPA 2016). Between 1990 and 2012, methane emissions in the US have increased by more than two-thirds due to notable industrialization of livestock farming associated with large concentrated animal feeding operations and waste lagoons (USEPA 2016). Second, factors like educational attainment and political ideology which are major contributors to public opinion and policy approach to environmental issues (Dietz et al. 2015; Zahran et al. 2006), have not been sufficiently analyzed despite their importance. Third, recent STIRPAT literature show that steady change in population age composition causes variations in energy consumption behavior and associated carbon emissions in developed countries (e.g., Liddle and Lung 2010; Menz and Welsch 2012). Zagheni (2011) integrates IPAT framework and environmental input–output analysis to assess the effect of population age structure on CO_2 emissions and studies the case of US using household level data for the year 2003. The study finds that per capita CO_2 emissions increase with age till 65–69, and then emissions are likely to decrease. Like other developed countries, the US is also experiencing the population aging problem as the average life expectancy increased from 68 years to 79 years in the time-period 1950–2013 (Mather et al. 2015). The percentage of people aged 65 and older has increased steadily from 9% in 1960 to become 15% in 2014 and is projected to be 24% by 2060 (Mather et al. 2015). Zagheni (2011) projects that the anticipated change in US population age distribution in next four decades is likely to have a small but visible positive impact on CO_2 emissions. However, existing literature on carbon emissions impact of population aging problem is sparse, and we aim to find new insights on this empirical question. Last but not the least, spatial variability in relationships among emissions and their determinants is a modeling issue as well. This spatial heterogeneity could be due to differences in societal factors that influence lifestyles, or state-level policies. In the context of US, Aldy (2005) assesses whether the relationship between per capita income and per capita CO_2 emissions is equal across the states for the 1960–1999 period, and shows that this relationship varies across the states. Although Videras (2014) has identified that determining what causes this regional variability in the US is an area for future research, till date no paper has taken up this issue.

This paper aims to contribute to the existing literature in the following ways. To the best of authors' knowledge, this is the first STIRPAT type panel data analysis focusing on per capita GHG as a whole in the context of US. In this paper, along with typical covariates used in a STIRPAT analysis we augment a few important factors like cattle population density, percentage of senior citizens in total population, and degree days.[3] Last but not the least, the present study investigates the reasons behind spatial heterogeneity in the relationship between emissions and their determinants across the US. In particular, this study aims to answer the following questions: do the emissions elasticities differ significantly in (1) pro-environmental states contrasted with the rest, and (2) more educated as opposed to less educated states? The rest of this paper is arranged as follows: Sect. 2 presents a short literature review focusing on the recent carbon STIRPAT and related studies for the US and

[3] Heating degree days (HDD) and cooling degree days (CDD) are used in calculations pertaining to building energy consumption (US Energy Information Administration 2012).

other developed countries; Sect. 3 describes econometric method, data used, and empirical model specifications; Sect. 4 explains estimation results; and Sect. 5 concludes with a discussion on policy perspectives.

2 Brief literature review

There exists a plethora of STIRPAT studies and extensions on CO_2 emissions in the context of developed and developing world (e.g., Fan et al. 2006; Liddle 2015). Many of these studies have focused on various econometric modeling approaches and factors that could influence emissions apart from traditional determinants used in a typical STIRPAT study. For instance, Jorgenson et al. (2016) use panel data on 50 US states for the time period 1990–2012 to investigate the relationship between state-level residential carbon emissions and income inequality. They find that emissions elasticity of the income inequality measure (Theil Index) is 0.43. They argue that positive association between CO_2 emission and income inequality in the US might be attributable to political economy effect and Veblen effect. In political economy effect, wealthy societies use their political influence to avoid carbon-control measure, whereas Veblen effect leads affluent households to overconsume the goods and services which are highly energy intensive for competing the overall status in the society. Videras (2014) estimates a STIRPAT model using US county-level total CO_2 emissions data for the year 2002 and geographically weighted regression technique which allows the relationship between regressand and regressors to vary over counties. He uses data from 48 contiguous states and estimates his model controlling for climatic conditions by including average temperature of three coldest and three warmest months in the set of regressors. The presence of strong spatial heterogeneity in the emissions elasticities of various socioeconomic factors is found. Estimated elasticities vary in magnitude across the conterminous US and sometimes they differ in direction also. For instance, the southeastern states are found to have negative income elasticities—a finding that goes against standard STIRPAT results.

Few studies using cross-country panel data have indicated that age structure affects energy-related CO_2 emissions. For example, Liddle and Lung (2010) employ STIRPAT model on panel data consisting of 17 OECD countries spanning the time period of 1960–2005, to find that population's environmental impact differs across the age group and older age group influences emissions negatively. Relationship between renewable energy use and CO_2 emissions too has been overlooked most of the time. Using data on OECD countries from 1980 to 2011, Shafiei and Salim (2014) show that in the long run renewable energy consumption has a negative effect on CO_2 emissions, whereas non-renewable energy consumption increases CO_2 emissions. After performing Granger causality analysis, they find that there is a unidirectional causality from CO_2 emissions to renewable energy consumption, whereas bidirectional causality exists from non-renewable energy consumption to CO_2 emissions. Recently, Squalli (2017) examines the relationship between renewable energy, coal, and GHG emissions utilizing US state-level data for the year 2010. He estimates separate STIRPAT models for CO_2, methane, and nitrous oxide emissions to find that a 10% increase in renewable energy share leads to 0.26% drop in methane emissions. Moreover, if coal is used for baseload power, mitigation of nitrous oxide emissions requires curbing the share of coal use in energy production at the state-level below 41.47%.

Auffhammer and Steinhauser (2007) look into the role of legislators in the context of modeling probability of voluntary emissions cutbacks in the US. They introduce a novel regressor—the League of Conservation Voters (LCV) scorecard indicator—which measures state-wise yearly percentage of favorable voting by elected representatives of the House and the Senate on environmental legislations. They find that the probability of an individual state proposing voluntary emission cutbacks positively depends on LCV score of the state in both the Senate as well as the House. Along the same line, Dietz et al. (2015) introduce a new regressor 'environmentalism' in the typical STIRPAT model and use state-level panel data covering the time period 1990–2007. Environmentalism is being captured by a state's Congressional delegation voting on the environmental issues. In other words, it captures the acceptance of environmental movement's goals by part of the society which in turn being reflected in the politics and finally policies of the state. Their results suggest that although environmentalism alone does not have an effect on emissions, the combined impact of time trend and environmentalism is significant. This finding is indicative of the role of political goodwill to ameliorate the climate change impacts of the scale of economic activity.

3 Materials and methods

3.1 Econometric method

This paper employs a modified STIRPAT framework to investigate the driving factors behind changes in per capita GHG emissions, following the approach adopted by the majority of macro-environmental modeling type research. The two major complications of many panel data STIRPAT models are: (i) probable non-stationarity of observables and unobservables; and (ii) likely heterogeneity in the impact of observables and unobservables on emissions across cross-sectional units. In a panel STIRPAT analysis, many variables can show strong trends over time (O'Neill et al. 2012). Homogeneity of model parameters is unlikely to hold across a large group of cross-sectional units. Moreover, if panel data have in-built cross-sectional dependence, estimating panel regression models with homogeneous slope coefficients may yield biased estimated coefficients (Sadorsky 2014). Panel regression models with heterogeneous parameters can be estimated using various mean group (MG) estimators. The MG approach incorporates heterogeneity by permitting all slope coefficients and error variances to vary across cross-sectional units (Pesaran and Smith 1995). The MG approach applies ordinary least squares (OLS) regression method to each cross-sectional unit to obtain state-specific slope coefficients and then averages these state-specific coefficients. Although the MG estimator (Pesaran and Smith 1995) specifically accounts for heterogeneity, it may suffer from issues like autocorrelation and cross-sectional dependence. Recent empirical studies have also mentioned the presence of spatial dependence in the CO_2 emissions data across the contiguous US (Clement and Elliot 2012; Roberts 2011; Videras 2014).

The Pesaran and Smith (1995) MG estimator does not take care of cross-sectional dependence and non-stationarity. A new variant of MG estimator—augmented mean group (AMG) estimator—accounts for both of these issues (Eberhardt and Bond 2009; Eberhardt and Teal 2010). It accounts for cross-sectional dependence by inclusion of a 'common dynamic process' in the cross-sectional unit regression, representing mean evolution of unobserved common factors across all units (e.g., technological improvement, urbanization, intensification of livestock farming, increasing per capita consumption of meat and dairy products in our case). In the first step of AMG approach, pooled OLS regression is run with T–1 year dummies in first differences and coefficients of year dummies are obtained. Each of the state regression models is then augmented with this new variable representing the common dynamic processes. Finally, the state-specific model parameters obtained in second step are averaged across the states, following MG approach. Sadorsky (2014) and Liddle (2015) have previously used AMG estimator while modeling energy intensity and carbon emissions elasticities, respectively. We employ AMG estimator by utilizing the xtmg command written for STATA (Eberhardt 2012). In addition, we utilize robust option with the xtmg command to construct the coefficient averages across states, which puts less emphasis on the outliers while computing the average of coefficients.

3.2 Empirical models and data

A modified STIRPAT model, where emissions are represented in terms of per capita can be written as:

$$ln\left(\frac{I_{it}}{P_{it}}\right) = \alpha_i + \beta_1 \ln A + \sum_{k=2}^{K} \beta_k \ln X_{kit} + \varepsilon_{it} \tag{1}$$

where *I, P, A, X, α, i,* and *t* represent environmental impact (GHG emissions), total population, affluence (represented by per capita State Gross Domestic Product or SGDP), other regressors, state-specific heterogeneity, state and year indicators, respectively, and ε denotes residual. Other regressors include renewable energy share, elderly population share, HDD + CDD index, and cattle density for which appropriate explanations and data sources are provided in the subsequent paragraphs. As recent econometric research on carbon emissions finds that an inverted-U relationship with per capita income (*a.k.a.* Environmental Kuznets curve) is unlikely for per capita carbon emissions (Liddle 2015), we do not include a quadratic term for *lnA* in Eq. (1). In the context of deciding whether to incorporate a proxy for the technology variable explicitly or not, we follow the arguments by York et al. (2003b) and Wei (2011) that no proxy for technology is free of controversy and say that technology embedded in residual terms makes the model consistent with the original IPAT framework. Nonetheless, one of the widely accepted proxies for the technology variables is energy intensity defined as total energy used per unit of GDP (Liddle 2015). But then, some scholars (Itkonen 2012; Jaforullah and King 2017) argue that CO_2 emissions estimates are implicitly calculated from the total energy use. Hence, incorporation of the energy use as a determinant of the emissions could lead to the endogeneity problem and consequently biased parameter estimates. Moreover, they also assert that total energy use and output produced in an economy might be highly correlated which in furtherance could change the magnitude and sign of the estimated coefficient of the former. In this regard, they clearly mandate that incorporation of total energy use as an independent determinant of CO_2 emissions should cease. Zhu and Peng (2012) argue that the incorporation of different technology proxies has ended up with wide range of elasticity values of fundamental explanatory variables like GDP. Hence, in our adjusted STIRPAT model we do not use an explicit proxy for technology (e.g., Zhu and Peng 2012).

We presume that there are groups in the population (in this case, full sample of 48 states) and entities (here, states) in these groups behave in dissimilar ways. But we do not have a prior knowledge regarding the variable which detects these groups. Let us assume that political support for an environmental cause and educational attainment of the citizens may be good classifiers. In other words, we wish to categorize states based on their political and educational profile (observables) into different homogeneous groups of emitters so that we can figure out whether the driving forces behind per capita GHG emissions have differential impacts in these groups or not. To account for the heterogeneity in population arising from these factors, we partition the full sample twice with respect to two controlling factors: an indicator of political support to environmental causes; and educational attainment. Forty-eight states are ranked with respect to each of these factors, and top 20 and bottom 20 in each list are considered as HIGH and LOW group of states with respect to the particular factor. Details of these four created groups are provided later.

The data employed in the current study are a balanced panel of 48 states covering time period of 25 years (1990–2014). Dependent variable is per capita GHG emissions in metric tons of CO_2 equivalent (MT). State-level aggregated emissions data are retrieved from the World Resources Institute (WRI 2017). The WRI provides data on per capita GHG emissions without land use change and forestry for the time period 1990–2014. Real per capita SGDP data are sourced from the Bureau of Economic Analysis (BEA), US Department of Commerce. Attributable to the change in GDP accounting methodology, we merge two real SGDP data series, one covering the span of 1990–1996 at constant 1990 prices and another covering years 1997–2014 at constant 1997 prices. Following Dietz et al. (2015), we recalibrate the 1990–1996 real SGDP series by getting a slope coefficient and constant term after regressing 1997 SGDP values from newer series (1997–2014) on the values from the older series (1990–1997).

Renewable energy share in total energy consumption is retrieved from the State Energy Data System, US Energy Information Administration. Disaggregated population statistics, i.e., elderly population (age ≥ 65 years) share in total population data, are retrieved from the estimates provided by the US Census Bureau. Data on state-level aggregate HDD and CDD are taken from the Climate Prediction Center, National Weather Service. We obtain HDD + CDD index as simple sum of the HDD and CDD following Sivak (2008) who argues this index to be the simplest possible climatological variable to model the change in energy demand due to climatic conditions. National Agricultural Statistics Service of the US Department of Agriculture provides state-wise estimates on number of cattle. Moreover, state-wise land area in square mile is extracted from the US Census Bureau to arrive at the cattle density defined as the number of cattle per square mile.

Following Dietz et al. (2015), this paper assumes that ideology of members of Congress reflects state political ideology and uses pro-environmental voting behavior by the state Congress members to appraise the environmental concern in the respective state. The LCV compiles data on each state's respective congressional voting toward environmental issues and tabulates Senate score and House score for various years, and makes the data available online. Average of these two scores gives us environmentalism scores for each state over the time period 1990–2014. Consequently, a unique indicator of pro-environmental attitude for each state is generated by averaging the yearly environmentalism scores over the time span of study. Based on that state-level mean environmentalism score, we rank 48 states and then partition the sample in two groups (see Fig. 3): top 20 pro-environmental states (hereinafter, ENV_HIGH) and bottom 20 states (hereinafter, ENV_LOW) to investigate whether the emissions elasticities pertaining to covariates of interest vary according to more homogenous groups controlling for political ideology and attitude to environment. Note that most states in ENV_LOW group are historically strong Republican states.[4]

[4] We call a state 'Strongly Republican' if the state is carried by the Republican Party in at least three of the four presidential elections (years: 2000, 2004, 2008, 2012).

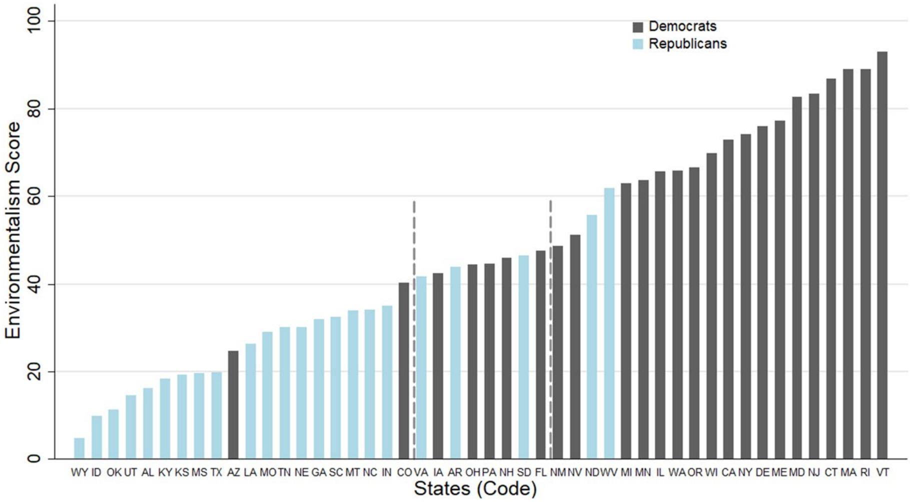

Fig. 3 State-level average environmentalism score

Moreover, Figs. 2 and 3 show that states which are historically inclined toward Democrats, such as California, Massachusetts, New York, and Washington, are more concerned about the environment (reflected by high environmental score), and emitted less per capita GHG than other states in 2014. Whereas, strong Republican states such as Georgia, Texas, and Utah (with low environmental score) emitted comparatively higher per capita GHG. Thus, political ideology has a strong influence on attitude to environment and hence per capita GHG emissions. For the other dividing factor (level of higher education), same strategy is applied for sample partitioning. We collect educational attainment data from the US census Bureau and concentrate on the 'highly educated' group defined as percentage of the population aged 25 years and above having bachelor's degree or higher. When higher education status is used to split the sample, top 20 states' and bottom 20 states' groups are titled as EDU_HIGH and EDU_LOW, respectively.

4 Empirical results and discussion

Interesting insights could be obtained from summary statistics based on the full and partitioned samples which are given in Table 1. Mean and median measures are shown to convene the differences between variables of interest among the groups at the beginning and end of the study period. A decline in per capita GHG emissions, over the study period, is noticed for all three sample categories (A–C). Per capita SGDP and elderly population percentage rise significantly in all groups, whereas cattle density shows a negative trend. A very small portion of energy use comes from renewables, and insignificant expansion has taken place from 1990 to 2014. For both years, i.e., 1990 and 2014, mean GHG per capita emission comes out to be considerably lower in ENV_HIGH and EDU_HIGH groups as compared to their counterparts. To test whether the concerned samples (two in this case) are coming from a population with same central tendency (or, location of the distribution), we focus on median in the place of mean as the sample size is small (20 states in a particular year). Null hypothesis of the Median test is that the samples are drawn from populations

Table 1 Descriptive statistics for selected years

Variable	Year	Measure	A: Full sample (48 states)	B: Split regarding environmentalism status		C: Split regarding educational attainment status	
				ENV_HIGH	ENV_LOW	EDU_HIGH	EDU_LOW
GHG per capita (MT)	1990	Mean	31.01	25.20	38.70	20.70	38.60
		Median	24.51	17.48	35.02	17.23	28.12
	2014	Mean	29.45	24.00	36.10	17.90	36.50
		Median	21.95	14.41	29.58	13.49	28.58
SGDP per capita ($)	1990	Mean	33,157	36,501	30,643	37,682	30,084
		Median	32,333	37,239	30,263	36,920	29,831
	2014	Mean	47,238	51,607	43,439	52,654	41,692
		Median	46,172	52,900	43,191	52,900	41,671
Renewable energy (%)	1990	Mean	0.79	0.90	0.68	0.83	0.81
		Median	0.43	0.37	0.31	0.37	0.63
	2014	Mean	1.00	1.12	0.80	1.01	1.04
		Median	0.65	0.67	0.65	0.63	0.67
Elderly population (%)	1990	Mean	12.66	12.66	12.05	12.14	13.03
		Median	12.65	12.78	12.48	12.30	12.65
	2014	Mean	15.04	15.34	14.32	14.49	15.51
		Median	15.04	15.21	14.44	14.44	15.26
Heating degree days	1990	Mean	1937	2165	1733	2061	1732
		Median	1928	1982	1475	1982	1663
	2014	Mean	1957	2168	1729	2057	1795
		Median	2022	2056	1702	2030	1702
Cooling degree days	1990	Mean	1100	688	1455	778	1372
		Median	835	600	1446	716	1222
	2014	Mean	999	628	1341	696	1262
		Median	730	475	1301	604	1179
Cattle density	1990	Mean	30.62	22.10	35.60	26.60	32.50
		Median	27.15	19.37	27.15	25.25	29.44
	2014	Mean	26.98	18.20	32.10	23.40	28.30
		Median	22.18	16.36	24.30	18.42	24.54

with same median. Comparison of median values shows that ENV_HIGH and EDU_HIGH groups emit less per capita GHG than their counterparts. In addition, median test corroborates these findings for the ENV_HIGH and EDU_HIGH groups.[5] Said otherwise, statistically different median values in the partitioned samples corroborate our choice of sample partitioning and motivate to estimate group-specific regressions in order to see whether

[5] Details of Median test results are as follows. Results from environmentalism-based partition: (a) Year = 1990, $\chi^2(1) = 6.4$; Probability > $\chi^2 = 0.01$; (b) Year = 2014, $\chi^2(1) = 6.4$; Probability > $\chi^2 = 0.01$. Results from educational attainment-based partition: (a) Year = 1990, $\chi^2(1) = 3.6$, Probability > $\chi^2 = 0.05$; (b) Year = 2014, $\chi^2(1) = 6.4$, Probability > $\chi^2 = 0.01$.

Table 2 Augmented mean group estimates for pooled US sample (48 states)

Variables	Full sample (Model 1)
ln SGDP per capita	0.0717** (0.0347)
ln Renewable energy share (%)	−0.0526*** (0.0121)
ln Elderly population share (%)	0.0276*** (0.00343)
ln HDD + CDD	0.0309*** (0.00781)
ln Cattle density	0.134*** (0.0410)
Common dynamic process	1.084*** (0.0989)
Constant	1.729*** (0.378)
RMSE	0.026
Observations	1200
Number of states	48

Standard errors in parentheses

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

Table 3 Augmented mean group estimates for partitioned samples

Variables	ENV_HIGH (Model 2)	ENV_LOW (Model 3)	EDU_HIGH (Model 4)	EDU_LOW (Model 5)
ln SGDP per capita ($)	0.102* (0.0548)	0.128** (0.0522)	−0.158** (0.0676)	0.135*** (0.0343)
ln Renewable energy share (%)	−0.0632*** (0.0156)	−0.0356* (0.0187)	−0.0576*** (0.0185)	−0.0471** (0.0210)
ln Elderly population share (%)	0.0842*** (0.00972)	0.0283*** (0.00545)	0.103*** (0.0131)	−0.00370 (0.00388)
ln HDD + CDD	0.0401*** (0.00764)	0.0307* (0.0163)	0.0202* (0.0108)	0.0212* (0.0123)
ln Cattle density	0.107* (0.0647)	0.119** (0.0571)	0.0877 (0.0721)	0.194*** (0.0614)
Common dynamic process	1.123*** (0.136)	1.016*** (0.138)	1.129*** (0.139)	0.932*** (0.133)
Constant	1.283* (0.662)	1.420** (0.605)	3.652*** (0.735)	1.366*** (0.371)
RMSE	0.030	0.021	0.030	0.024
Observations	500	500	500	500
Number of states	20	20	20	20

Standard errors in parentheses

***$p < 0.01$; **$p < 0.05$; *$p < 0.1$

that leads to different emissions elasticities. Table 2 shows regression results for the contiguous US (Model 1), and Table 3 elicits the regression results for environmentalism and educational attainment-based partitioned datasets (Models 2–5). Detailed analytical discussion on estimated models is presented in the following paragraphs.

Let us first focus on results from Model 1 (based on full sample) shown in Table 2. In this model, per capita SGDP, elderly population share, HDD + CDD index, and cattle density affect emissions positively. On the other hand, renewable energy share influences emissions negatively. Regression coefficient of a log transformed regressor used in a STIRPAT model is to be interpreted as 'ecological elasticity' (York et al. 2003b) which in our case measures the proportional change in per capita GHG emissions due to a one percent change in that regressor, while other factors are held constant. The estimated coefficient values are indicative of inelastic relationships, where impact is less responsive to changes in a particular regressor. A 1% increase in per capita SGDP leads to a 0.0717% increase in GHG emissions, net of the effects of other covariates. Elasticity with respect to the older population share is found to be 0.027. Positive and significant elasticity of the older population share is in agreement with the findings by Zagheni (2011) who estimates that aging of the US population will cause CO_2 emissions to rise marginally until 2050. Elasticity for renewable energy share is − 0.053, meaning that emissions decline in lesser proportion to an increase in the renewable energy share. A negative elasticity for renewable energy share is also reported by Shafiei and Salim (2014) in their STIRPAT study on OECD countries. Elasticity with respect to the HDD + CDD index comes out to be around 0.031, and a positive elasticity for HDD + CDD index is in the line with literature (Aldy 2005; Auffhammer and Steinhauser 2007; Marcotullio et al. 2013). Elasticity with respect to cattle density is reported to be 0.134. Among the considered regressors, cattle density evidently appears to be the most important driver of per capita GHG emissions in 48 adjoining states. There is strong presence of common dynamic process in the data, which can be thought of as characteristics of technological change and socioeconomic transitions (Eberhardt and Teal 2010).

Table 3 provides regression results for the environmentalism-based groups 'ENV_HIGH' and 'ENV_LOW' (Models 2 and 3), and educational attainment-based groups 'EDU_HIGH' and 'EDU_LOW' (Models 4 and 5). To start with, let us focus on results from environmentalism-based partitioned samples. Emissions elasticity of per capita SGDP comes out to be 0.128 with statistical significance in the 'ENV_LOW' panel, while it remains weakly significant in the 'ENV_HIGH' group with a relatively lower value of 0.102. It implies that rise in affluence may not play a noteworthy role in driving emissions in the 'ENV_HIGH' group. There are some more interesting observations. Elasticities of the share of elderly population having age more than or equal to 65 come out to be different as well, 0.084 and 0.028 for the 'ENV_HIGH' and 'ENV_LOW' group of states, respectively. Elasticity of the renewable energy share comes out to be -0.063 and -0.035 for the 'ENV_HIGH' and 'ENV_LOW' group, respectively, but statistical significance is weak in the later case. It signifies that renewable energy may not have played a noteworthy role in bringing down state-level per capita emissions in the 'ENV_LOW' group of states, because of its infinitesimal presence. Emissions elasticities for the HDD + CDD index are found to be significant with value of 0.04 for the 'ENV_HIGH' sample, but weakly significant in the 'ENV_LOW' sample. Now coming to the cattle density, its elasticity comes out to be weakly significant for 'ENV_HIGH' states but emerges to be significant in its counterpart with a value of 0.119. Coefficient for common dynamic process is significant in both cases. If we focus on strong statistical significance ($p < 0.05$) then among the considered driving forces, elderly population share emerges as the factor with highest elasticity value in the 'ENV_HIGH' group, whereas per capita SGDP has the highest elasticity in the 'ENV_LOW' group.

Next, we move to Model 4 and Model 5, estimated models for the state groups ‘EDU_HIGH’ and ‘EDU_LOW,’ respectively. First, we focus on the emissions elasticity of per capita SGDP which comes out to be 0.135 and − 0.158 for the ‘EDU_LOW’ and ‘EDU_HIGH’ group correspondingly. Evidently, states with higher proportion of graduates do experience decrease in emissions with increasing affluence ceteris paribus. Renewable energy share influences emissions negatively with elasticities as − 0.057 and − 0.047 for the ‘EDU_HIGH’ and ‘EDU_LOW’ samples individually. Older population share affects emissions positively with elasticity of 0.103 in the ‘EDU_HIGH’ group, whereas it remains insignificant in the ‘EDU_LOW’ group. The coefficient of HDD + CDD index comes out to be weakly significant in both samples with values around 0.02, whereas the coefficient of cattle density is positive and significant for the ‘EDU_LOW’ group only. As usual, coefficient for common dynamic process is significant in both cases. If we focus on strong statistical significance ($p<0.05$) then among the considered driving forces, elderly population share again emerges as the most important factor behind emissions in the ‘EDU_HIGH’ group (similar to the case of ‘ENV_HIGH’ states), whereas cattle density has the highest elasticity in the ‘EDU_LOW’ group.

Summarizing all of the empirical outcomes reported in this paper, the following salient facts emerge. First, cattle density and per capita SGDP are identified to be major drivers of per capita GHG emissions in the US. Second, although societal factors like educational attainment and politics are not introduced as separate explanatory variables to maintain enough degrees of freedom in regression models, they play substantial role in order to form homogenous groups over which estimates of major ecological elasticities would vary significantly. Third, we observe that increasing affluence does not always result in higher emissions. One percent increase in per capita SGDP in ‘EDU_HIGH’ group will lead to a fall in per capita GHG emissions. In fact, if a strict criterion ($p<0.05$) is used, one can infer that further rise in per capita SGDP in ‘ENV_HIGH’ group will not lead to significant change in emissions. Fourth, renewable energy share impacts emissions negatively with low elasticity values in the range (− 0.047, − 0.063). Fifth, aging population affects emissions positively with elasticity values in the range (0.028, 0.103) and has a major role in some states (common states in ‘ENV_HIGH’ and ‘EDU_HIGH’ groups).

Results associated with sample partitioning exercise have some policy implications. These partitioned samples and related model estimations enable us to identify a set of states which are performing better and a set of states which are posing serious challenges in order to achieve GHG reduction targets. The first set consists of common states in ‘ENV_HIGH’ and ‘EDU_HIGH’ groups. This ‘leaders’ group comprises of 13 states: California, Connecticut, Delaware, Illinois, Maryland, Massachusetts, Minnesota, New Jersey, New York, Oregon, Rhode Island, Vermont, and Washington. Excepting Illinois, other states are part of the US Climate Alliance initiative as of now. Whereas the second set of states are common states in ‘ENV_LOW’ and ‘EDU_LOW’ groups. This ‘laggards’ group is made up of 11 states: Alabama, Idaho, Indiana, Kentucky, Louisiana, Mississippi, North Carolina, Oklahoma, South Carolina, Tennessee, and Wyoming. According to the latest US Energy Information Administration data, Wyoming and Kentucky appear in the list of top five states that supply about 70% of the US total coal production. McDermott (2009) observes that maximum use of that coal takes place in energy sector and most of that demand comes from the middle and southeastern parts of the US. States which do not belong to any of these two groups are designated as ‘average performers’. Figure 4 depicts these best, average, and worst performer states, and one can see a high concentration of ‘laggards’ in the southern US.

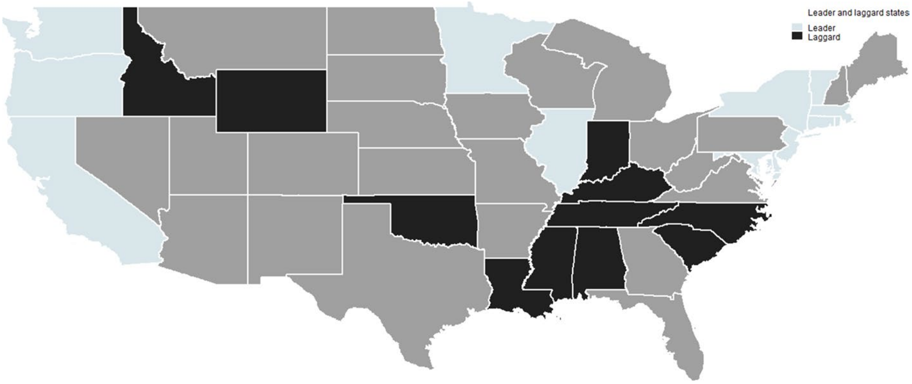

Fig. 4 Leader and laggard states in the context of GHG emissions performance

Except for Indiana, none of these 'laggards' has adopted 'Energy Efficiency Resource Standard'[6] (EERS) and only Oklahoma and Indiana have accepted 'Renewable Portfolio Standard' (RPS) as per a government report (US Department of State 2014). However, North Carolina joined the US Climate Alliance initiative recently. The 'laggards' group requires special attention from policymakers if they wish to put a check on future GHG emissions from these states. A matter of concern is that some of these 'laggards' are also the states experiencing a steady rise in human and cattle population. Idaho and South Carolina rank 9th and 10th, respectively, in population growth over 2010–2016 according to the most recent estimates available from the US Census Bureau. Moreover, Idaho ranks 3rd and 4th in growth of cow population and average herd size, respectively, over 2006–2016 (Progressive Dairyman 2017). The success of GHG mitigation initiative in the US looks bleak unless the stakeholders succeed to mold public attitude toward climate change by spreading awareness and providing economic incentives to adopt low carbon lifestyle in the 'laggard' states. Following Dietz et al. (2015), politics can play a vital role in adoption of climate change policies like EERS and RPS as soon as possible to ameliorate the effects of the scale of economic activity.

5 Conclusion

To the best of authors' knowledge, this article presents the first panel data analysis of state-level per capita GHG emissions in the US for the period 1990–2014. This study offers modest contributions to the related STIRPAT literature at least in two ways. First, we incorporate a novel explanatory variable—cattle population density—in estimating a version of the STIRPAT equation to consider the important role of growing livestock sector, a hitherto understudied and overlooked factor. Second, our research provides classification of states into more homogeneous groups and finds heterogeneity in emissions elasticities

[6] EERS emphasizes on long-term energy savings target by achieving certain percentage reduction in the total energy sales from energy efficiency measures. RPS requires that electric utilities are supposed to produce certain percentage of the total electricity generated from renewable sources. Interested reader may refer to Carley and Browne (2013) for details.

in terms of (i) political attitude toward environment and (ii) educational attainment. We accommodate presence of inter-state heterogeneities by partitioning the conterminous US in four groups (top 20 states and bottom 20 states with respect to each of the above-mentioned social factors), and employing heterogeneous slope parameters panel data model for each group. We successfully categorize states based on their political behavior and education profile into different types of emitters (high intensity or 'laggards' and low intensity or 'leaders').

Regression results based on the full sample suggest that per capita SGDP, cattle population density, population share of senior citizens, and degree-days impact per capita GHG emissions positively whereas share of renewable energy in the total energy consumption affects emissions negatively. Cattle density and per capita SGDP are identified to be major drivers of per capita GHG emissions in the contiguous US. Estimations based on created groups of states indicate that these factors impact emissions differently across these groups. Broadly, they vary in magnitude and sometimes differ in direction too. For instance, emissions elasticity for per capita SGDP is negative for top 20 states with respect to percentage of adults having completed graduation. Thus, an increase in the overall educational attainment of the society may play a pivotal role to mitigate GHG emissions. Findings from our grouping analysis suggest that in a diverse country like US, policymakers should not focus on the average relationships dictated by a single STIRPAT equation, but should account for regional differences if they want accuracy and higher effectiveness in federal policymaking. In order to lower GHG emissions, the stakeholders have to focus on those states which are lagging behind in educational attainment and convince the public, politicians, and legislators of these states to implement green energy policies. Political attitude to climate change will play a big role in the future, especially in the 'laggard' states. It has been observed that scientific information-based propaganda has had a negligible effect on public concern about the threat of climate change, while political mobilization by elites and advocacy groups play a crucial role in this matter (Brulle et al. 2012). Thus, as voiced by Ripple et al. (2014), political will to commit resources to mitigate energy emissions and control growing livestock sector is highly warranted in order to fight climate change.

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