U.S. state-level carbon dioxide emissions: Does it affect health care expenditure?

Nicholas Apergis*, Rangan Gupta**, Chi Keung Marco Lau*** and Zinnia Mukherjee****

ABSTRACT

This paper is the first to provide an empirical analysis of the short run and long run effects of carbon dioxide (CO_2) emissions on health care spending across U.S. states. Accounting for the possibility of non-linearity in the data and the relationship among the variables, the analysis estimated various statistical models to demonstrate that CO_2 emissions led to increases in health care expenditures across U.S states between 1966 and 2009. Using quantile regressions, the analysis displayed that the effect of CO_2 emissions was stronger at the upper-end of the conditional distribution of health care expenditures. Results indicate the effect of CO_2 emissions on health care was relatively stronger for states that spend higher amounts in health care expenditures. The primary policy message of the paper is that there can be tangible health related benefits associated with policies that aim to reduce carbon emissions across U.S. states.

Keywords: health care expenditure, carbon dioxide emissions, panel cointegration, panel quantile regression

JEL Classification: I18, C31, C33

* Corresponding author. Department of Banking and Financial Management, University of Piraeus, Piraeus , Greece. Email: napergis@unipi.gr.
** Department of Economics, University of Pretoria, Pretoria, South Africa. Email: rangan.gupta@up.ac.za
*** Newcastle Business School, Northumbria University, Newcastle upon Tyne, UK. Email: chi.lau@northumbria.ac.uk.
**** Department of Economics, Simmons College, , Boston, , USA. Email: zinnia.mukherjee@simmons.edu.

1. Introduction

The relationship between environmental quality and healthcare has long been an area of interest among scholars. Studies from medical science provide evidence that air pollution affects all types of mortality. For example, Wordley et al. (1997) find that in the U.K., ambient outdoor concentrations of PM10 significantly affect numerous health indicators. Schwartz and Dockery (1992) use data over the period 1973–1980 for Philadelphia air pollutants, such as total suspended particulate (TSP) and sulfur dioxide increased daily mortality rates. Spix and Wichmann (1996) show that in Koln, sulfur dioxide leads to 3-4% increase in mortality and particulates to a 2% increase in mortality. Controlling for intercity differences, Ostro and Rothschild (1989) make use of Health Interview Surveys to find that the association with small particulate matter can lead to work loss and even bed disability in adults. However, providing evidence about the short- and long-run effects of pollutants on health is often very challenging. Levels of exposure to pollutants are often unknown, given the lack of effective monitoring systems. The length of exposure to air pollutants, multiple exposures to different pollutants, and the cumulative effects of exposures all pose difficulties in fully understanding the impact of each pollutant on human health (Briggs, 2003).

From an economic perspective, a key issue of both academic and policy interest is the potential spatial and temporal effects of different environmental quality indicators on healthcare expenditures. Economists have long been interested in identifying the determinants of healthcare expenditures. Early studies, such as Abel-Smith (1967), show that income is a key driver of healthcare spending. Murthy and Ukpolo (1995) document that U.S. per capita health expenditure and its determinants are cointegrated. Using data from 1960–1987, they find that certain exogenous factors such as per capita income, health services and Medicare prices, age, and practicing physicians are key determinants of health care spending. Focusing on Canada, Matteo and Matteo (1998) find that both income and age have a positive effect on per capita provincial healthcare expenditure.

While a relatively large body of literature exists on the determinants of health care expenditure, the empirical literature on the relationship between environmental quality indicators and health care expenditure is still limited in spite of the fact that the relationship between the effects of environmental quality indicator on health has important economic and social implications. The externalities generated by air pollution have negative consequences for labor productivity, which has direct implications for industrial performances and national output. Hansen and Selte (2000) are among the first to study the relationship between environmental quality and labor productivity. Using data from Oslo, they find that an increase in small particulate matter (PM) leads to a rise in sick leaves, which negatively affects output and trade in the city of Oslo. However, they illustrate that these effects of sulfur dioxide and nitrogen dioxide on sick leaves are rather ambiguous. Jerrett et al. (2003) make use of data for 49 counties in Ontario and a sequential two-stage regression model to find that counties with higher pollution tend to experience higher health expenses, while counties that spend more on protecting environmental quality have lower expenditures on health care.

Narayan and Narayan (2008) are the first to examine the role of environmental quality in explaining per capita health expenditure for a number of OECD countries. The authors adopt a panel cointegration approach to estimate both the short-run and long-run effects of environmental quality on health care expenditure for eight OECD countries. They find that per capita health expenditure, per capita income, carbon monoxide emissions, and sulfur oxide emissions are panel cointegrated. Interestingly, they find that in the short-run, both income and carbon monoxide emissions have a positive and statistically significant effect on health expenditure. In the long-run, income has an elastic and positive effect, while carbon monoxide and sulfur oxide have an inelastic and positive impact on health expenditure. Assadzahed et al. (2014) focus specifically on the relationship between carbon dioxide emissions and health care expenditure. They make use of a panel dataset for eight oil exporting countries over the period 2000–2010. Their results reveal that short-run elasticities for income and carbon dioxide are positive and statistically significant, while the effect of life expectancy on health expenditures turns out to be negative.

This paper focuses on the relationship between carbon dioxide and health care expenditures. Carbon dioxide emissions play a major role in defining current and long-term global environmental quality. Greenhouse gases trap heat in the atmosphere. There are four greenhouse gases: carbon dioxide (CO_2), methane (CH4), nitrous oxide (N2O), and fluorinated gases, such as hydrofluorocarbons, perfluorocarbons, sulfur hexafluoride.[1] Larger emissions of greenhouse gases lead to higher concentrations of pollutants in the atmosphere. Scientific evidence shows that carbon dioxide can stay trapped in the earth atmosphere for a very long time. The Global Warming Potential (GWP) is a measure widely used to assess the effect of greenhouse gases in the atmosphere. Specifically, it shows the amount of heat trapped in the atmosphere by a greenhouse gas over an interval of time. Typically, the time period used for calculating GWPs is 100 years. Carbon dioxide emissions can increase atmospheric concentrations of CO_2 that can last for thousands of years, much longer than other greenhouse gases. In fact, CO_2 is used as a reference against which GWPs of all other greenhouses are measured. This makes it critically important to develop our understanding of the role of carbon dioxide emissions in human health over time. The negative externalities stemmed from carbon dioxide emissions have welfare effects that affect both economic growth and human welfare.

[1] Source: U.S. EPA: http://www3.epa.gov/climatechange/ghgemissions/gases.html

Therefore, this paper contributes to the environmental and health economics literature by providing an empirical analysis of the impact of per capita CO_2 emissions on real per capita health care expenditure across all the 50 U.S. states, controlling for a measure of output (i.e., real per capita personal disposable income), given the widespread evidence of the latter being a strong predictor of health care expenditures (Freeman, 2003, 2012; Caporale et al., 2015). The U.S. is the second largest emitter of carbon dioxide behind China and ahead of the European Union (EU) and India.[2] Within the U.S., there is a considerable variation in CO_2 emissions across states. For example, in 2013, aggregate CO_2 emissions in Texas for all five sectors, i.e. commercial, industrial, residential, transportation, electric power, was 712.86 million metric tons, whereas for Vermont was 5.97 million metric tons.[3] There is also some variation in per capita health care spending across these states. For example, in 2009, the per capita health care spending in the District of Columbia (D.C.), Alaska, and Massachusetts were $10348.85, $9127.63, and $9277.89, respectively, indicating the highest spending per capita across all U.S. states. In comparison, per capita health care spending for Utah, Georgia and Idaho were $5030.94, $5467.46, and $5657.99, respectively, three states with the lowest per capita spending in the country.[4]

The novelties of this paper are twofold. First, it is the first to provide an empirical analysis of the short- and long-run effects of CO_2 emissions of healthcare spending across U.S. states using a panel dataset. The results can be useful in the context of designing and evaluating U.S. health care and environmental policies, particularly, those that account for cross-state variation. Second, the paper makes a methodological contribution as well. To account for the possibility of non-linearity in the data of the individual variables as well as in the relationship amongst the variables, we estimate various conditional mean-based statistical

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[2] Source: Union of Concerned Scientists: http://www.ucsusa.org/global_warming/science_and_impacts/science/each-countrys-share-of-co2.html#.VtNOmfkrLIU
[3] Source: U.S. EPA - https://www3.epa.gov/statelocalclimate/resources/state_energyco2inv.html
[4] Data source: http://kff.org/other/state-indicator/health-spending-per-capita/#

models. We also conduct quantile regressions to account for the variability of the results across the US states, conditioned on their level of health care expenditures.

The remainder of the paper is organized as follows: In Section 2, the data set is discussed, while Section 3 details the empirical model used in the analysis, as well as the discussion of the empirical findings. Finally, Section 4 provides concluding remarks and policy implications.

2. Data

For the empirical analysis, the study makes use of annual data on healthcare expenditures for all 50 US states for the period 1966 to 2009. Data were obtained from the Center for Medicare and Medicaid Services Health Expenditures by state of residence. This database reports total personal health care spending by state and by service. Data on nominal personal disposable income over the same time span are obtained from the regional database of the Bureau of Economic Analysis. Data on both these variables are expressed in per capita terms, by dividing with population figures, also obtained from the regional database of the Bureau of Economic Analysis.

Given that the state level CPI levels are not available over the entire period under study, the nominal per capita health care expenditure and the per capita nominal personal disposable income are converted to their real values by deflating with the aggregate US CPI. The data on real per capita health expenditures (H) and personal disposable income (INCOME) for the 50 US states are obtained from Freeman (2012) where a full description of the data set is available.[5] As far as data on per capita CO_2 is concerned, they come from the Carbon Dioxide Information Analysis Center, and are measured in thousand metric tons of carbon. Finally, data are transformed into their natural logarithmic values.

[5] We would like to thank Donald G. Freeman, Sam Houston State University, for providing the dataset.

3. The model and results

As is standard practice in panel data econometrics (N=50) with a long time series component (T=44), we start off by conducting unit root testing on the data. Given the evidence of non-linearity in the three variables of interest (Li et al., 2014; Caporale et al., 2015) and Zerihun et al., (forthcoming)), the analysis uses non-linear unit root tests along with standard linear versions. In case that unit root tests support non-stationarity, the analysis moves ahead with cointegration tests to analyze the relationship between health care expenditures and CO_2 emissions, after controlling for income.

Non-linear panel unit roots

Following Cerrato et al. (2011, 2013), the Data Generating Process (DGP) for the time series of interest y_{it}, is modeled through an Exponential Smooth Transition Autoregressive (ESTAR) model:

$$y_{it} = \xi_i y_{i,t-1} + \xi_i^* y_{i,t-1} Z(\theta_i; y_{i,t-d}) + \mu_{it} \quad t = 1,\ldots,T \quad i = 1,\ldots,N \text{,} \tag{1}$$

where,

$$Z(\theta_i; y_{i,t-d}) = 1 - \exp[-\theta_i (y_{i,t-d} - \chi^*)^2] \tag{2}$$

θ_i is a positive parameter and χ^* is the equilibrium value of y_{it}. Given the initial value of y_{it}, the error term μ_{it} has the one-factor structure:

$$\mu_{it} = \gamma_i f_t + \varepsilon_{it} \text{,}$$

$$(\varepsilon_{it})_t \sim i.i.d.(0, \sigma_i^2) \tag{3}$$

in which f_t is the unobserved common factor, and ε_{it} is the individual-specific (idiosyncratic) error. Following the literature, we set the delay parameter d to be unity and equation (3) in its first-difference form yields:

$$\Delta y_{i,t} = \alpha_i + \xi_i y_{i,t-1} + \sum_{h=1}^{h-1} \delta_{ijh} \Delta y_{ij,t-h} + (\alpha_i^* + \xi_i^* y_{i,t-1} + \sum_{h=1}^{h-1} \delta_{ih}^* \Delta y_{i,t-h}) * Z(\theta_i; y_{i,t-d}) + \gamma_i f_t + \varepsilon_{it} \tag{4}$$

Once we assert that $y_{i,t}$ follows a unit root process in the middle regime, of $\xi_i = 0$, Equation (4) can be rewritten as:

$$\Delta y_{i,t} = \xi_i^* y_{i,t-1} \left[1 - \exp(-\theta_i y_{i,t-1}^2)\right] + \gamma_i f_t + \varepsilon_{i,t} \tag{5}$$

We can form the null hypothesis of non-stationarity $H_0 : \theta_i = 0 \forall i$, against its alternative $H_1 : \theta_i > 0$ for i = 1,2,…, N_1 and $\theta_i = 0$ for $i = N_1 + 1, \ldots, N$. The fact that ξ_i^* is not identified under the null hypothesis, the null hypothesis cannot be tested. Cerrato *et al*. (2011) use a first-order Taylor series approximation methodology that re-parameterizes Equation (5) and the auxiliary regression yields:

$$\Delta y_{i,t} = a_i + \delta y_{i,t-1}^3 + \gamma_i f_t + \varepsilon_{i,t} \tag{6}$$

Equation (6) can be extended if errors are serially correlated:

$$\Delta y_{i,t} = a_i + \delta y_{i,t-1}^3 + \sum_{h=1}^{h-1} \vartheta_{ih} \Delta y_{i,t-h} + \gamma_i f_t + \varepsilon_{i,t} \tag{7}$$

Cerrato et al. (2011) further show that the common factor f_t can be approximated by:

$$f_t \approx \frac{1}{\tilde{\tilde{\gamma}}} \Delta \tilde{\tilde{y}}_t - \frac{\bar{b}}{\bar{\gamma}} \tilde{\tilde{y}}_{t-1}^3 \tag{8}$$

where $\tilde{\tilde{y}}_t$ is the mean of y_{it} and $\bar{b} = \frac{1}{N} \sum_{i=1}^{N} b_i$.

Combining Equations (7) and (8), it can be written as the following non-linear cross-sectionally augmented DF (NCADF) regression:

$$\Delta \bar{y}_{i,t} = a_i + b_i \bar{y}_{i,t-1}^3 + c_i \Delta \tilde{\tilde{y}}_t + d_i \Delta \tilde{\tilde{y}}_{t-1}^3 + \varepsilon_{i,t} \tag{9}$$

t-statistics could be derived from $\hat{b}_i$, which are denoted by:

$$t_{iNL}(N,T) = \frac{\hat{b}_i}{s.e.(\hat{b}_i)} \tag{10}$$

where $\hat{b}_i$ is the OLS estimate of $\hat{b}_i$, and $s.e.(\hat{b}_i)$ is its associated standard error. The *t*-statistic in Equation (10) can be used to construct a panel unit root test by averaging the individual test statistics:

$$\bar{t}_{iNL}(N,T) = \frac{1}{N}\sum_{i=1}^{N} t_{iNL}(N,T) \tag{11}$$

This is a non-linear cross-sectionally augmented version of the IPS test (NCIPS). The Pesaran (2007) test (CIPS) takes into account the cross sectional dependence among panel members. The results of NCIPS statistics are reported in Table 1 and they support the presence of a unit root across all three variables, while similar conclusions are reached through the CPIS test (Panel A, Table 2). Given that we provide evidence that all variables are I(1), we proceed to test the null hypothesis of no cointegration. Panel B in Table 2 reports the panel cointegration results. The first three cointegration tests assume cross sectional independence, indicative of no cointegration[6]. It is worth noting that the evidence of cointegration is stronger for the periods 1995 to 2009 and 1985 to 2009. One major reform is the Consolidated Omnibus Budget Reconciliation Act of 1985 (COBRA) that amended the Employee Retirement Income Security Act of 1974 (ERISA) to give some employees the ability to continue health insurance coverage after leaving employment. The health reform of the 'Health Security Express' started at the end of July 1994. It is shown to be influential as well.

[Insert Tables 1and 2 about here]

To check the robustness of our results, the analysis also makes use of the error-correction-based panel cointegration tests incorporating cross sectional dependence (Westerlund, 2007). Westerlund develops four normally distributed tests, namely G_t, P_a, and P_t. The first two tests

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[6] These tests are ADF-based and PP-based cointegration tests (Pedroni, 2000; Pedroni, 2004) and Kao (1999) ADF-based tests. All three tests suggest the rejection of the null of no cointegration.

are mean-group tests, since they only assume unit-specific error correction parameters, while the rejection of the null hypothesis can be taken as evidence of cointegration of at least one of the cross-sectional units. The latter two test statistics pool information overall the cross-sectional units and, hence, the rejection of the null should be taken as evidence of cointegration for the panel as a whole.

As another check for robustness, we make use of two tests (i.e., τN and ΦN) for the null hypothesis of no cointegration, proposed by Westerlund and Edgerton (2008); they take into account the presence of structural breaks within the heterogeneous panel. Panel A in Table 3 reports the break date for both level break and regime shift. The cointegration results in panel B document that the null of no cointegration is rejected at the 1% significance level in the no break model for both τN and ΦN tests.

[Insert Table 3 about here]

Given that panel cointegration results recommend the presence of a long-run relationship between health care expenditure, personal disposable income per capita and CO_2 emissions, the analysis estimates the long-run coefficients through the following model:

$$H_{it} = \alpha_i + \beta_i INCOME_{it} + \gamma_i CO2_{it} + e_{it} \tag{12}$$

$$e_{it} = \lambda_i' F_t + \mu_{it}, \tag{13}$$

where, the subscript '*it*' denotes the observation on the *i'th* state at time *t*, for *i=1,2,…,N and t=1,2,…,T.* The dependent variable H_{it} denotes real health care expenditures per capita, while $INCOME_{it}$ is real personal disposable income per capita; $CO2_{it}$ is CO_2 emissions per capita. All variables are represented in their natural logarithmic form. F_t is the mx1 vector of unobserved common factors. Three conventional estimation methods are used to estimate the long-run relationship, namely, the Mean Group (MG) (Pesaran and Smith, 1995), the Group

Mean Fully Modified OLS (GM-FMOLS) (Pedroni, 2000, 2001) and the Group Mean Dynamic OLS (GMDOLS) (Pedroni, 2001).

Moreover, the CD test of Pesaran (2004) confirms the presence of cross section dependence in the residuals for those three mean group methodologies (MG, GM-FMOLS, and GM-DOLS); the test results violate the assumption of cross-section independence (Table 4); therefore, we employ a novel general methodology which allows cross-sectional dependence and cross section-specific slope coefficients (i.e., CCE-MG methodology) proposed by Pesaran (2006) and Kapetanios et al. (2011). The CCE-MG estimator suggests that the coefficients are statistically significant at the 5% significant level.

[Insert Table 4 about here]

Autoregressive Distributed Lag (ARDL) model

This sub-section uses the autoregressive distributed lag (ARDL) model, proposed by Pesaran et al. (2001), to examine the relationship between real income per capita, real health expenditures, and per capita CO_2 across the 50 US states. It is worth noting that we pursue this approach to check out for the robustness of the above results. While the unit root tests indicate that the entire panel of the three variables are non-stationary, there are cases (i.e., states) where the variables are found to be stationary (similarly to the results in Freeman, 2012; Caporale et al., 2015). The advantage of the ARDL methodological approach is that it does not require pre-testing of unit roots, and hence, is a more general approach, while it accommodates for any possible issues of endogeneity that could be present. The ARDL representation of the effects of real income per capita and per capita CO_2 on real health expenditures can be described as follows:

$$\Delta H_{it} = \lambda_{0+} \sum_{i=1}^{m} \Delta\lambda_{1i}\ \Delta H_{it-1} + \sum_{i=1}^{m} \Delta\lambda_{2i}\ \Delta INCOME_{it-1} \sum_{i=1}^{m} \Delta\lambda_{3i}\ \Delta CO2_{it-1} + \lambda_4 H_{it-1} + \lambda_5 INCOME_{it-1} + \lambda_6 C02_{it-1} + \upsilon_{it} \tag{14}$$

where, m is the lag order and v_t is assumed to be an independent and identically distributed i.i.d. process with a finite second moment. Equation (14) can be transformed into an Error Correction model as follows:

$$\Delta H_{it} = \sigma_{0+} \sum_{i=1}^{k} \Delta\sigma_{1i}\ \Delta H_{it-1} + \sum_{i=1}^{k} \Delta\sigma_{2i}\ \Delta INCOME_{ti-1} \sum_{i=1}^{k} \Delta\sigma_{3i}\ \Delta CO2_{it-1} + \xi(H_{it-1} - \beta_1 INCOME_{it-1} + \beta_2 C02_{it-1}) + \mu_{it}$$

(15)

where, ξ is the speed of the adjustment parameter, and β_1, β_2 are the long-run coefficients for real income and CO_2 per capita, respectively. The short-run parameters are represented by σ_{1i} , σ_{2i} , and σ_{3i} . The ARDL (p, q, k) model is given by:

$$\Delta H_{it} = \sigma_{0+} \sum_{i=1}^{p} \Delta\sigma_{1i}\ \Delta H_{it-1} + \sum_{i=1}^{q} \Delta\sigma_{2i}\ \Delta INCOME_{it-1} \sum_{i=1}^{k} \Delta\sigma_{3i}\ \Delta CO2_{it-1} + \xi(H_{it-1} - \beta_1 INCOME_{it-1} + \beta_2 C02_{it-1}) + \mu_{it}$$

(16)

Table 5 presents the results for Equation (16); they illustrate that the error-correction coefficient is negative and statistically significant at the 1% significance level. Importantly, the long-run coefficients from the cointegrating equation are reported; a 10% increase in per capita income results in a long-run increase of 8.61% in per capita health expenditures, while a 10% increase in per capita carbon emissions results in a long-run increase of 1.57% in per capita health expenditures. The ECM coefficient is −0.319, implying that the adjustment speed is about 32%.

[Insert Table 5 about here]

Panel quantile regressions (PDQ)

In the relevant literature, OLS estimations have been used extensively to consider the determinants of health expenditures (Freeman, 2012). However, there are reasons to believe that the influence of income and per capita CO_2 emissions is likely to differ across states. We conduct the BDS test, with the statistics rejecting linearity in the majority of states across all three variables, indicating that some type of hidden structure is contained in the series. This is reinforced by the linearity test recommended by Tsay (1996).[7] Therefore, the panel quantile regression (PQR) methodology, in relevance to Equation (16), is pursued; it accounts for the likelihood of heterogeneity as it estimates the parameters of the model at different points on the (conditional) per capita health expenditure distribution. The non-linear nature of PQR allows us to estimate different parameters on the logarithms of income and CO2 for under-expenditures (regions at the lower end of the conditional per capita health expenditure distribution) and over-expenditures (those at the upper end). Further advantages of the PQR methodology include the non-sensitivity of estimated coefficients relating to outlier observations on the dependent variable of health expenditures, while the estimators are more efficient than those provided by OLS when the error term is not normally distributed.

Since the mean regression methodologies fail to take into account of the potential heterogeneous impacts, we specify the $\tau-$ th quantile ($0<\tau<1$) of the conditional

[7] Results are not reported here to save space, but available upon request.

distribution of the dependent variable (i.e., the log of per capital health expenditures), given a set of independent variables X_{it} , as follows:

$$Q_\tau\left(\frac{LnH_{it}}{X_{it}}\right) = \alpha_\tau + \beta_\tau X_{it} + \alpha_\tau \mu_{it} \tag{17}$$

where LnH_{it} is per capita health expenditure in a log form of state i at time t, and X_{it} represents a vector of two independent variables, i.e. income in a log form (i.e., $lnINCOME_{it}$) and per capita CO_2 emissions, also in its log form (i.e., $lnCO_{2it}$). u_{it} denotes unobservable factors, such as institutional and socio-demographic factors (e.g., unmeasured disease severity or other health limitations). The parameters in equation (17) are estimated by minimizing the absolute value of the residual using the following objective function:

$$Q_\tau(\beta_\tau) = \min_\beta \sum_{i=1}^{n} [|LnH_{it} - \beta_\tau X_{it}|]$$

$$= \min_\beta \left[\textstyle\sum_{i:LnH_{it} \geq \beta X_i} \tau |LnH_{it} - \beta_\tau X_{it}| + \sum_{i:LnH_{it} < \beta X_{it}} (1-\tau) |LnH_{it} - \beta_\tau X_{it}|\right], \tag{18}$$

One problem with the use of QR methods is the inclusion of a large number of fixed effects, with numerous studies discussing the problem of capturing unobserved factors through a fixed effects quantile model (Koenker, 2004; Canay, 2011). With a large number of cross-sectional units and a small number of observations for each cross-sectional unit, the estimated parameters of the fixed effects are not consistent. Koenker (2004) proposes a class of penalised QR estimators (i.e., the shrinkage methodology) to address the above problem by estimating directly a vector of individual effects. However, Canay (2011) finds that the Koenker's methodology is computationally intensive and he subsequently introduces a two-step methodology of estimating panel quantile regression models with fixed effects. In the first stage, the conditional mean of u_{it} is estimated and then the analysis employs the estimated parameters to obtain the individual fixed effect $\hat{\alpha}_i = \frac{\sum_{t=1}^{T}(LnH_{it} - X'_{it}\hat{\beta}_{\mu})}{T}$, where $\hat{\beta}_{\mu}$ are the estimated parameters from the conditional mean regression.

In the second stage, the analysis subtracts the estimated individual effect from the dependent variable, $\widehat{LnH}_{it} = LnH_{it} - \hat{\alpha}_i$ and then the standard estimation of the quantile regression is used. For parameters inference, Canay (2011) proposes a bootstrap procedure for estimating the variance-covariance matrix for this estimator. The bootstrap methodology is implemented by randomly drawn samples with the replacement of a sample of size NT from the original data and computing the two-step estimator, as described above for B times, resulting in a total of B different estimates. The estimated bootstrapped variance-covariance matrix at quantile τ is constructed as:

$$\frac{1}{B}\sum_{j=1}^{B}\left(\hat{\beta}_j^*(\tau) - \bar{\beta}^*(\tau)\right)\left(\hat{\beta}_j^*(\tau) - \bar{\beta}^*(\tau)\right)'$$

where $\hat{\beta}_j^*(\tau)$ are the estimated parameters from the *j*th bootstrap and the τth quantile, whereas $\bar{\beta}^*(\tau) = \frac{1}{B}\sum_{j=1}^{B}\hat{\beta}_j^*(\tau)$.

Table 6 reports the results from the QR approach by Canay (2011). The findings display the coefficients on the per capita health expenditures between the 10th and 90th quantiles when estimating Equation (17). When using panel quantile regression coefficients on per capita CO_2 emissions, the estimates tend to be relatively high at higher quantiles (i.e., for over-expenditure regions; those per capita health expenditures are high, given the values of the explanatory variables). The influence of 1% increase in per capita CO_2 emissions on per capita health expenditures is only 0.13% at the 10^{th} percentile, in comparison to 0.16% at the 90^{th} percentile. However, the coefficients on income tend to be slightly smaller at higher quantiles; the influence of 1% increase in income on per capita health expenditure is 0.61% at the 10^{th} percentile in comparison to 0.59% at the 90^{th} percentile.

[Insert Table 6 about here]

5. Conclusion

The determinants of health care expenditure have long been studied in the economics literature. One area that remains relatively less explored is the relationship between environmental quality and health care spending. This paper estimated the causal effect of carbon dioxide emissions on per capita health care expenditure across all U.S. states. Carbon dioxide is the primary greenhouse gas and is known to stay trapped for decades in the earth's atmosphere, which necessitates the need to understand its impact on human health. The U.S is the second largest emitter of CO_2 and exhibits a considerable variation in both CO_2 emissions and per capita health care expenditure across states. This paper contributed to the literature by providing for the first time a rigorous empirical analysis of the short- and long-term effects of CO_2 emissions on health care spending across U.S. states.

Realizing the possibility of non-linearity in the data of the individual variables as well as in the relationship amongst the variables, the analysis estimated various statistical models to show that CO_2 emissions increased health care expenditures. In addition, using quantile regressions, the analysis displayed that the effect of CO_2 emissions was stronger at the upper-end of the conditional distribution of health care expenditures. In other words, the effect of CO_2 emissions on health care was relatively stronger for states that spend higher amounts in health care expenditures.[8]

The results are expected to be highly interesting both in evaluating existing policies and designing future U.S. health and environmental policies that aim to capture cross state variations in environmental quality and health care outcomes, given that the effect of CO2 emissions is heterogeneous across states and is dependent on where the stats fall in terms of

[8] For example we observed that the average (from 1966 to 2009) of health care expenditure for Alaska is $1932 and the per capita CO2 is 14.83 metric tons. For Idaho the figure for health care expenditure is $1363 while the per capita CO2 is 3.63 metric tons for the time period over 1996 to 2009.

the health care expenditures. The primary policy message, however, emerging from the empirical findings is that the health benefits of policies that aim to reduce carbon emissions can more than pay for the costs associated with implementing these policies. In other words, the health care-associated savings, mostly from things like avoided hospital visits and reduced spending on pollution-related illnesses, from a carbon-reducing policy can be substantially higher than the cost it took to implement the policies. However, to achieve significant reductions at the lowest cost to the economy will require strong, coordinated, economy-wide actions that begin soon. In fact, the Clean Power Plan, fully supported and implemented by President Obama, establishes the first-ever national standards to limit carbon pollution from power plants. Although, certain limits that protect public health by reducing soot and other toxic emissions have been set on a national basis, existing power plants, the largest source of carbon emissions in the U.S., are still able to release as much carbon pollution as they want. By setting carbon pollution reduction goals for power plants and enabling states to develop tailored implementation plans to meet those goals, this plan is considered to be a strong, flexible framework that will manage to provide, mostly, significant public health benefits, along with a number of other targets, such as to: create tens of thousands of jobs while ensuring grid reliability, drive more aggressive investments in clean energy technologies, save the average American family a certain amount of money on their annual energy bill by 2030, give a head start to wind and solar deployment and prioritize the deployment of energy efficiency improvements in low-income communities that need it most, and continue American leadership on climate change by keeping it on track to meet the economy-wide emissions targets it has set.

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Table 1. Nonlinear panel unit root test results (NCIPS)

States	lnH	lnCO2	lnINCOME
Alabama	0.2281	-0.6296	-0.4173
Alaska	-1.2728	-0.9185	-1.9742**
Arizona	-2.2031	-1.0420	-1.6987
Arkansas	-0.5635	-3.0873***	-0.0142
California	-1.5961	-1.4477	-1.0819
Colorado	-2.1183***	-1.3036	-0.6376
Connecticut	-0.9418	-1.9567**	-1.0490
Delaware	-0.6795	-0.6418	-1.6152
Florida	-1.6404	-1.0436	-1.8622
Georgia	-0.5410	-1.5568	-1.7974
Hawaii	-1.8919	-2.5422***	-2.0403***
Idaho	-0.6640	-0.6576	-1.4348
Illinois	-0.6708	-1.1427	-0.3145
Indiana	-0.3513	-2.7062***	-0.9864
Iowa	-1.2861	-1.6210	-2.7583***
Kansas	-1.4415	-0.5033	-0.5024
Kentucky	-0.7987	-1.3769	-1.2238
Louisiana	-0.7154	-1.8805	-1.5103
Maine	-0.1249	-2.3277***	-1.3601
Maryland	-1.3286	-2.0348**	-2.0571***
Massachusetts	-1.8555	-2.7840***	-2.9790***
Michigan	-0.8053	-1.2608	-0.6291
Minnesota	-2.1724***	-0.8490	-1.7785
Mississippi	-0.1562	-1.8917	-2.6489***
Missouri	-2.0276	-1.0366	-2.1741***
Montana	-1.8244	-1.5028	-1.4937
Nebraska	-1.5302	-2.5234***	-3.3648***

Nevada	-1.9666**	-0.8284	-1.1182
New Hampshire	-0.9716	-2.5431***	-1.3798
New Jersey	0.1557	-2.9379***	-1.5312
New Mexico	-1.4389	-2.4254***	-0.5335
New York	-1.4054	-0.4861	-1.8177
North Carolina	-0.1883	-0.6752	-1.3827
North Dakota	-2.0016**	-0.9644	-1.4556
Ohio	-0.6865	0.5596	-0.6247
Oklahoma	-1.5786	-0.9153	-1.6319
Oregon	-2.3474***	-1.3173	-0.4397
Pennsylvania	-0.9866	-1.7410	-1.1888
Rhode Island	-1.3137	-1.5499	-2.2142***
South Carolina	-0.0655	-1.0599	-1.9088*
South Dakota	-1.7900	-2.0728**	-1.9273*
Tennessee	-0.7978	-1.1999	-0.0643
Texas	-2.2012***	-0.4324	-1.3550
Utah	-1.4523	-1.7071	-1.2776
Vermont	-0.8074	-2.3887***	-2.1440***
Virginia	-1.3209	-1.8505	-2.2531***
Washington	-2.0600***	-2.2630***	-0.8430
West Virginia	-0.3119	-0.2882	-1.2910
Wisconsin	-1.3015	-2.4041***	0.3709
Wyoming	-1.3757	-1.1364	-1.0535
AVERAGE	-1.0307	-1.0828	-1.0817

Critical values of Panel NCADF Distribution (N = 50, T = 44):

1%	-3.68
5%	-3.04
10%	-2.76

Critical Values of Individual NCADF Distribution (N = 50, T = 44):

1%	-2.05

5%	-1.96
10%	-1.91

Note: Critical values are from table 13. and table 14. of Cerrato et al., (2011).***, **, & * denote 1%, 5%, & 10% critical values respectively.

Table 2. Panel unit root test results

Test		lnH	$lnCO_2$	lnINCOME
Panel A: Panel Unit Root Test				
CIPS		-1.715	-2.447	-1.981
NCIPS		-1.184	-1.498	-1.409
Panel B: Panel Cointegration				
	(1966-2009)	(1990-2009)	(1995-2009)	(1985-2009)
Pedroni-ADF	-3.517***	-7.837***		
with trend	-3.273***	-6.701***		
Pedroni-PP	-1.474*	-6.981***		
with trend	0.1749	-5.790***		
Kao-ADF	-6.041***	-5.658***		
Gt	-1.435	-1.941	-3.957	-2.533***
Ga	-9.662**	-7.423**	-0.563**	-7.711***
Pt	-6.907	-10.968	-5.685***	-15.603***
Pa	-4.919	-5.919*	-0.338***	-6.383***

Note: CIPS denotes the Pesaran (2007) panel unit root test. NCIPS is the nonlinear version of CIPS from Cerrato et al. (2011). Pedroni-ADF, Pedroni-PP, Kao-ADF, stand for Pedroni (2000; 2004) ADF-based and PP-based, and Kao (1999) ADF-based cointegration tests respectively. Ga,Gt, Pa, and Pt stand for the cointegration tests of Westerlund (2007). The tests proposed by Westerlund (2007) account for cross sectional dependence and was calculated through the calculation of robust standard errors by boostrapping with 1000 replications. The null hypothesis of the reported cointegration tests is "no cointegration". The Pa and Pt test statistics pool information overall the cross-sectional unitsRejection of H0 should therefore be taken as evidence of cointegration for the panel as a whole. Since cross sectional units are suspected to be correlated, robust critical values can be obtained through bootstrapping.

Table 3. Panel unit root test with structural changes

Panel A: Break date for level shift and regime shift

States	Break Date (level break)	Break Date (regime shift)
Alabama	1998	1971
Alaska	1980	1980
Arizona	1995	1970
Arkansas	1991	1991
California	1980	1980
Colorado	1993	1980
Connecticut	1980	1980
Delaware	1979	1979
Florida	1982	1976
Georgia	1986	1986
Hawaii	1997	1979
Idaho	1991	1991
Illinois	1991	1991
Indiana	1980	1980
Iowa	1991	1991
Kansas	1991	1991
Kentucky	1991	1991
Louisiana	2000	1982
Maine	1980	1980
Maryland	1998	1972
Massachusetts	1980	1980
Michigan	1979	1976
Minnesota	1991	1991
Mississippi	1991	1991

Missouri	1991	1982
Montana	1991	1991
Nebraska	1980	1980
Nevada	1980	1980
New Hampshire	1980	1980
New Jersey	1980	1980
New Mexico	1991	1979
New York	1983	1971
North Carolina	1980	1980
North Dakota	1980	1980
Ohio	1982	1981
Oklahoma	1991	1991
Oregon	1980	1980
Pennsylvania	1979	1979
Rhode Island	1980	1980
South Carolina	1991	1991
South Dakota	1980	1980
Tennessee	2006	2006
Texas	1994	1973
Utah	1980	1980
Vermont	1986	2002
Virginia	1992	1992
Washington	2002	1979
West Virginia	1991	1991
Wisconsin	1986	1986
Wyoming	1991	1991
AVERAGE	1987	1983

Panel B: Panel cointegraton with structural break

(1966-2009)	τN		ΦN	
Model	Value	p-value	Value	p-value

No break	-0.098	0.461	1.826	0.966
Level break	-0.965	0.167	0.884	0.812
Regime shift	-0.008	0.497	1.831	0.966
(1995-2009)				
No break	-2.74	0.003	0.009	0.008
Level break	1.549	0.939	0.009	0.504
Regime shift	-0.699	0.242	0.398	0.655

Notes: The test is implemented using the Campbell and Perron (1991) automatic procedure to select the lag length. We use three breaks, which are determined by grid search at the minimum of the sum of squared residuals. The p-values are for a one-sided test based on the normal distribution.

Table 4. Mean group estimations and residual tests

		α	β	γ
MG		1.264	0.202	0.2
		[0.001]	[0.017]	[0.00]
CD test	86.85			
	[0.007]			
MG-FMOLS			0.224	0.233
			[0.002]	[0.00]
CD test	32.22			
	[0.00]			
MG-DOLS			0.332	0.331
			[0.004]	[0.00]
CD test	7.504			
	[0.00]			
CCE-MG	-0.59	0.093	0.242	0.041
	[0.557]	[0.836]	[0.001]	[0.047]

Notes: Figures in square brackets denote p-values. Equation (12) was estimated with. Fully Modified OLS (Pedroni, 2000, 2001) and Group Mean Dynamic OLS (Pedroni, 2001). MG, GM-FMOLS, and GM-DOLS stand for standard Mean Group (Pesaran and Smith, 1995), Group Mean Fully Modified OLS (Pedroni, 2000, 2001) and Group Mean Dynamic OLS (Pedroni, 2001).MG, GM-FMOLS and GM-DOLS assume cross section independence. CCE-MG refers to the Common Correlated Effects Mean Group estimation and inference method (Pesrasan, 2006) and allows for cross sectional dependence.CD-test refers to the Pesaran's (2004) test of cross sectional dependence.

Table 5. ARDL estimation results

Selected Model: ARDL(2, 4, 4)

Dependent Variable: D(LNH)

Variable	Coefficient	Std. Error	t-Statistic	Prob
	Long Run Equation			
LNINCOME	0.8611	0.0543	15.8539	0
$LNCO_2$	0.1576	0.0263	5.9812	0
	Short Run Equation			
COINTEQ01	-0.3119	0.0321	-9.7176	0
D(LNH(-1))	0.2021	0.0316	6.3977	0
D(LNINCOME)	-0.2851	0.0587	-4.8605	0
D(LNINCOME(-1))	-0.3068	0.0619	-4.9566	0
D(LNINCOME(-2))	-0.0510	0.0634	-0.8039	0.4218
D(LNINCOME(-3))	0.0513	0.0490	1.0464	0.2957
D($LNCO_2$)	-0.0377	0.0188	-2.0071	0.0452
D($LNCO_2$(-1))	-0.0915	0.0214	-4.2812	0
D($LNCO_2$(-2))	-0.0076	0.0209	-0.3635	0.7164
D($LNCO_2$(-3))	-0.0122	0.0216	-0.5670	0.5709
C	-0.5685	0.0658	-8.6367	0
Time Trend	0.0049	0.0007	7.3414	0

Table 6. Quantile estimation of the relationship between personal health care expenditures, personal disposable income, and CO2 emissions in per capita form

Variables	Fixed Effect quantile regression								
	10%	20%	30%	40%	50%	60%	70%	80%	90%
Per capita C02 in log	0.1319***	0.1299***	0.1363***	0.1413***	0.1376*	0.143***	0.1442***	0.1531***	0.1632***
	('0.0123)	(0.0098)	(0.0085)	(0.0064)	(0.0064)	(0.0062)	(0.0063)	(0.0070)	(0.0099)
Per capita GDP in log	0.6079***	0.6333***	0.6124***	0.6174***	0.6059***	0.5913***	0.5912***	0.5917***	0.6076***
	(0.054)	(0.0375)	(0.0324)	(0.02785)	(0.0242)	(0.0233)	(0.0268)	(0.0329)	(0.0248)

Note: Bootstrap SEs in parentheses with 2000 replications. * significant at 10% and *** at 1%. OLS SEs are robust. The number of observations is 2200.