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On the examination of the decoupling effect of air pollutants from economic growth: A convergence analysis for the US

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Abstract

The objective of this study is to examine the convergence patterns of decoupling factors of three environmental hazards (CO_2, SO_2, and NO_X) from economic growth across the U.S. regions over the period 1990-2017. By applying the Phillips and Sul (2007, 2009) methodology, we unravel convergence clubs and illustrate their transition paths. The generic algorithm rejects the convergence hypothesis for the whole sample, justifying the existence of several formulated convergence clubs among the US regions. The empirical findings further elucidate the existence of two "*large*" spatial clusters concerning the CO_2 and SO_2 decoupling indicators (Club 2 and Club 1 respectively). Lastly, the transition paths validate the P-S convergence test results, while we provide some useful policy implications.

Keywords: Decoupling; Ecological footprint; Convergence analysis; Air pollutants; Economic growth.
JEL Codes: O44; O51; R11.

1. Introduction

The term decoupling was first adapted to literature by Zhang (2000) and presented as an indicator by the OECD (2002) report, which distinguishes between two types of decoupling effect: the absolute (when the environmental variable moves to the opposite direction from economic growth at a stable or decreasing trend) and the relative (when the environmental variable is positive but at a slower rate than the growth of economic activity) decoupling effect. It is used to characterize the link between economic growth and environmental deterioration (Kemp-Benedict, 2018). To put it differently, decoupling presents a disruption between the rate of growth of environmental damage and economic growth in each period. According to UNEP (2011), the impact of decoupling is referring to a growth path under which a region can increase its economic growth by having specific policies under which the environmental pressures will deteriorate.

Tapio (2005) presents a theoretical framework by defining the difference between decoupling, coupling, negative as well as weak, strong, and expansive/recessive degrees of decoupling[1]. Particularly, the growth of the variables under scrutiny (environmental & economic activity) can be positive or negative, expressed as expansive coupling (growing link) and recessive coupling (recession link), while decoupling may be divided into three categories such as weak, strong, and recessive decoupling. Negative decoupling may also be broken down to strong, weak, and expansive negative decoupling[2].

Phillips and Sul (2007) have developed a regression-based convergence test by constructing a method of clustering panels into club convergence groups. With this test, the authors provide a framework of asymptotic representations for the factor components that enables the development of econometric procedures of estimation and testing. Phillips and Sul (2009) allow

[1] For other concepts of decoupling see, *inter alia*, Vehmas et al., (2003).
[2] For more details about the framework presented by Tapio (2005) see Table 1.

in traditional neoclassical models for cross-section heterogeneity among economies and evolution in rates of technological progress over time. The authors examine transitional behavior among economies that includes convergence to a common steady-state path as well as various forms of transitional divergence and convergence.

In this paper, we evaluate the impact of decoupling for the U.S. regions over the period 1990-2017 by utilizing the concepts of decoupling effect proposed by Tapio (2015) and the methodological framework of Phillips and Sul (2007, 2009). For this purpose, we use deflated regional GDP data, and we construct the decoupling indices for one global carbon dioxide- CO_2 and two local nitrogen oxides-NO_X and sulfur dioxide- SO_2 pollutants for the 50 U.S. states and the District of Columbia (DC).

The contribution of this study is twofold. First, we examine the decoupling effect for the 51 US regions over the period 1990-2017. Second, we use the methodological framework of Phillips and Sul (2007, 2009) to explore the existence of possible convergence clubs. To the best of our knowledge, this is the first study to assess the convergence/divergence hypothesis on the (de)coupling of environmental pressure-volume growth (ΔCO_2, ΔSO_2, and ΔNO_x) from economic growth (ΔGDP). As a result, the present work fills the gap in the empirical literature by providing fresh evidence of convergence/divergence among regions with estimated decoupling indicators. The empirical findings could be useful for government officials and policymakers toward their efforts to combat environmental degradation and climate change alongside economic growth. This could be achieved by a significant shift from fossil fuels (e.g., coal, oil) to "*clean*" energy resources such as renewables (wind, hydro, solar power) and natural gas.

The rest of the paper proceeds as follows. Section 2 discusses the literature on the decoupling effect and Section 3 presents the data and the methodology used in this paper. Section

4 provides the empirical findings, while Section 5 concludes the paper.

2. Literature Review

Studies on the decoupling effect fall into three main categories. First, there exist studies examining decoupling factors in a large set of countries with little or no sectoral disaggregation and a specific environmental variable, that is, mainly CO_2 emissions; second, there exist studies on decoupling effect in specific sectors of the economy, third, there exist studies on decoupling effect in specific countries and fourth, there exist studies that examine the decoupling factors in a large set of countries with sectoral disaggregation and a set of environmental variables. Most of the studies are based on the OECD (2002) report, but some of them use only the framework proposed by Tapio (2005) or both.

Regarding the first category, the report by OECD (2002) indicates different decoupling states among OECD countries. Particularly, the report explores 31 different decoupling indicators and finds that the relative decoupling effect is widespread for GHG emissions concerning GDP, while the absolute decoupling effect occurs in several countries for air and water pollution relative to GDP and population during the period from 1990 to 1999.

Diakoulaki and Mandaraka (2007) use decomposition analysis to explain changes in industrial CO_2 emissions and to evaluate the progress made in 14 EU countries in decoupling emissions from industrial growth emissions for the period before and following the agreement on the Kyoto Protocol (1990-2003). They found considerable but not sufficient decoupling effort for most of the EU countries, mostly in the pre-Kyoto Protocol period. Mazzantia and Zoboli (2008) find no decoupling effect between waste generation and income growth for EU25 member states from 1995 to 2005. The authors conclude that even though complete decoupling is far from being achieved, especially for waste generation, there are signs of effective EU waste policies implemented in the late 1990s and early 2000s. Brinkley (2014) indicates nine countries that present the decoupling effect of economic growth from carbon emissions over the period 1970-2008. Reasons for the observed CO_2 decoupling effect may be the substitution of coal and oil with natural gas in Denmark and the Netherlands, or in other countries, such as Belgium, decoupling was achieved through increased energy imports.

Raupach et al. (2007) analyze CO_2 decoupling trends from 1980 to 2004 and find that high-income countries present a relative decoupling effect, whereas some developing countries exhibit stronger, others weaker or no decoupling trend. The authors also argue that the decline in decoupling trend is both due to less improvement in energy intensity of GDP, and CO_2 intensity of energy during the period from 2000 to 2004, compared to the period from 1990 to 1999. Kojima and Bacon (2009) examine the decoupling effect for 122 countries around the world from 1996 to 2006. The authors state that almost one-fifth of the countries under scrutiny managed to achieve absolute decoupling of CO_2 emissions from economic growth. They find a higher global decoupling coefficient of CO_2 emissions from GDP growth during 1994–2001, compared to the 2001–2006 period. Also, there is evidence that decoupling trends of air emissions in the EU vary strongly by country and sector. Knight and Schor (2014) examine the decoupling effect of CO_2 from GDP in 29 high-income countries from 1991 to 2008 and conclude that decoupling trend between GDP and territorial CO_2 emissions is present for the period examined, but not for consumption-based emissions.

Moutinho et al. (2018) examine decoupling elasticity between CO_2 emissions, and economic growth for 16 Latin American countries, according to five-year periods, from 1994 to 2013. The analysis indicates mixed results from the decoupling analysis, indicating that the changes of the CO_2 emissions are due to other economic and environmental factors rather than to an effect of the GDP growth. Mikayilov et al. (2018) examine decoupling elasticities for 12 western European countries and find mixed results. Particularly, the authors find evidence in favor of relative decoupling in 8 out of the 12 European countries, while for the remaining 4 countries, the income elasticity of CO_2 emissions is more than unity.

Wang and Zhang (2021) explore the effect of trade openness on decoupling carbon emissions from economic growth in 182 countries around the world during the period from 1999 to 2015. The empirical results show that trade openness positively (negatively) impacts the decoupling economic growth from carbon emission in rich (poor) countries. The authors argue also that the increase of individual income and population negatively affects the decoupling process, while renewable energy and high oil prices contribute to the decoupling economic growth from carbon emissions.

Concerning the second category, that is, studies on decoupling effect in specific sectors of the economy, Finel and Tapio (2012) examine the transport sector in 141 countries from 1975 to 2005 and find mixed evidence of decoupling trends. The authors divide the countries into the eight forms of decoupling proposed by Tapio (2005). The empirical results indicate that the two largest groups of countries exhibit weak negative decoupling, where both emissions and GDP grew, but the emissions grew at a faster rate than GDP and weak decoupling, where again both emissions and GDP grew, but this time GDP grew faster than the emissions.

Ren and Hu (2012), following Tapio's (2012) methodological framework examine the decoupling effect in Chinese's nonferrous metals industry for the period 1996–2008.[3] The empirical results show that the Chinese nonferrous metals industry has gone through four decoupling stages: strong negative decoupling stage (1996–1998), weak decoupling stage (1999–

[3] See also Li et al. (2017) for a study on decoupling effect of China's textile sector.

2000), expensive negative decoupling stage (2001–2003), and weak decoupling stage (2004–2008). The authors argue that the main reason for emissions mitigation is the reduction of energy intensity. Tang et al. (2014) explore both the effect of tourism transportation, accommodation, and activities on the total CO_2 emissions of the tourism industry and the decoupling effects between tourism-related CO_2 emissions and the tourism economy in China over the period 1990–2012. The empirical results show that tourism transportation is the most important factor contributing to the CO_2 emissions of the tourism industry. Concerning the decoupling effect, the results show negative and weak decoupling during the study period. Vlontzos et al. examine the decoupling effect on EU25's primary sectors and find evidence of mixed results. Particularly, the authors examine the period from 2001 to 2008 and argue that the sub-period 2001–2006 covers the fully coupled with specific cultivations period for subsidy administration, while the second sub-period 2007–2008, a new decoupled subsidy scheme was implemented.

The third category concerns studies devoted to the assessment of the decoupling effect in various countries. Vehmas et al. (2003), examine the decoupling effect in Brazil and find weak decoupling between primary energy supply and economic growth, but an expansive recoupling between CO_2 emissions from fuel consumption and economic growth between the period 1993-1999. Climent and Pardo (2007) examine the relationship between GDP and energy consumption in Spain from 1984 to 2003 and conclude that the latter plays an important role as a limiting factor for economic growth in the short run. De Freitas and Kaneko (2011) examine the decoupling effect between the growth rates in economic activity and CO_2 emissions from energy consumption in Brazil from 2004 to 2009 and compare the results with the ones derived from 1980 to 1994. The empirical results show several periods of decoupling effect in Brazil and provide similarities of decoupling effect for the period 1980 to 1994. The authors also utilize a log-mean Divisia index

(LMDI) framework to identify the determinants of emissions change. The decomposition analysis indicates that carbon intensity, energy mix, and modifications in the economic structure, are the main determinants of emissions reduction in Brazil between 2004 and 2009.

Sorrell et al. (2012) estimate that UK achieved relative but not absolute decoupling of road freight energy consumption from GDP during the period from 1989 to 2004. According to the researchers, the main factor contributing to the decoupling effect is the declining value of manufactured goods relative to GDP. Sjöström and Östblom (2010) argue that to offset the effect of economic growth on waste generation in Sweden, the intensities of material-related wastes and waste related to firms' production and households' consumption must decrease at a lower rate than Sweden's historically estimated reduction rate. Andreoni and Galmarini (2012) examine the decoupling effect in five sectors of economic activity in Italy from 1998 to 2006 and find (do not find) evidence of relative (absolute) decoupling effect of carbon dioxide emissions concerning energy consumption. Wang et al. (2014) find the decoupling effect of CO_2 emissions in China from 1996 to 2004, but no comparable trends between 2005 and 2011. Particularly, decoupling elasticity values of energy-related carbon emissions and economic growth increase from 0.53 in 1996 to 0.85 in 2011, indicating a weak decoupling effect from 1996 to 2004 and an expansive recoupling effect from 2005 to 2011.[4] Muangthai et al. (2014) examine the decoupling effects of CO_2 emissions from Thailand's thermal power sector and argue that find evidence of the decoupling effect of energy consumption and CO_2 emissions between 2000 and 2005. Conrad and Cassar (2014) examine the decoupling effect of energy intensity, climate change, air quality, water, waste, and land, from GDP (per capita and population) in Malta from 2000 to 2005. The authors argue that there exists more evidence of relative decoupling than evidence of absolute decoupling,

[4] See also Zhang and Da (2015) and Wu et al. (2016).

but variation in the magnitude of decoupling factors.

Roinioti and Koroneos (2017) examine, *inter alia*, the decoupling relationship between CO_2 emissions and economic growth in Greece. The empirical results show yearly periods of weak and strong decoupling from 2003 to 2010, but no evidence of decoupling from 2011 to 2013. Particularly, weak decoupling is achieved in periods 2003–2004, 2004–2005, 2006–2007, and 2009– 2010, while strong decoupling appears only in periods 2005– 2006, 2007–2008, and 2008–2009. In the most recent years (2010–2011, 2011–2012, and 2012–2013), during Greece's economic contraction, the decoupling effect is absent. The authors conclude that the decoupling effect achieved in the previous years is intercepted during the years of recession, indicating a strong connection between economic growth and CO_2 emissions.

Yang et al., (2018) examine the decoupling effect between industrial growth and CO_2 emissions in China from 1996 to 2015 by using the LMDI method and Tapio's (2005) methodological framework. The empirical results show a reverse U tendency of decoupling progress, moving from strong decoupling to weak decoupling, and turned back to strong decoupling in the manufacturing sector, while expansive coupling and strong negative decoupling appeared in construction, transportation, and commercial sectors over certain sub-periods under the examined period. The authors point out that even though the critical factor for the reduction of CO_2 emission is energy intensity, this effect is not observable in all the regions examined throughout the period under scrutiny. Yang and Yang (2019) following Tapio's (2005) framework find weak decoupling between resource consumption, pollution emissions, and economic growth is the main characteristic at present (from 2006 to 2016) after undergoing through large fluctuation from 1979 to 2006.[5]

[5] See also Grand (2016) and Vergara et al. (2013) for decoupling analysis in Argentina and Latin America and Caribbean correspondingly.

Regarding the fourth category, that is, studies that examine the decoupling factors in a large set of countries with sectoral disaggregation and a set of environmental variables, Tapio (2005) uses data to examine the relationship between GDP, passenger traffic, freight transport volume, and CO_2 emissions in the EU15 countries. The empirical results for EU 15 countries show a change from expansive negative decoupling to expansive coupling concerning passenger transport, and from weak decoupling to expansive negative decoupling concerning freight transport. UK, Sweden, and Finland exhibit weak decoupling in the 1990s. The author also uses the same data to examine the relationship between GDP, passenger traffic, freight transport volume, and CO_2 emissions in Finland between 1970 and 2001. The empirical results show weak decoupling of GDP from road traffic volume and strong decoupling of road traffic volume and CO2 emissions from road traffic between 1990 and 2001. The author suggests four possible explanations regarding the causes of the empirical results for Finland, that is, sustainable mobility, green urban lifestyle, increasing income differences, and statistical misinterpretation.

Naqvi and Zwickl (2017) examine the decoupling effect from economic performance, measured by real value-added, of production-based emissions for 18 EU countries in six economic sectors (electricity, manufacturing, transport, agriculture, financial and non–financial services) and six pollution indicators (energy use, CO_2, SO_X, NO_X, NH_3, and PM_{10}) from 1995 to 2008. [6] The authors analyze two sub-periods, 1995–2001 and 2001–2008, and find evidence of decoupling in the median EU country for almost all sectors and decoupling factors, except electricity sector and NH_3 emissions. Indeed, regarding energy use and CO_2 emissions, the sector of manufacture exhibits the strongest median country decoupling performance, while NO_X and PM_{10} emissions show decoupling patterns. The results in Germany, France, and Great Britain indicate that the

[6] This sector includes mining and quarrying, construction, and wholesale and trade.

highest decoupling factors are observed for SO_X. By analyzing also, a modified decoupling framework proposed by Tapio (2005),[7] the authors find high diversity in decoupling effect and unclear patterns of development trends. While some countries and sectors present absolute decoupling in the first sub-period (1995–2001), not all these present the same status in the second sub-period (2001–2008).

From the above-mentioned literature review it is evident that most of the studies examine the decoupling effect in China or regions of China, European Union or countries from the European Union (Greece, Spain, Italy) and other studies have examined the decoupling effect in specific countries around the world (i.e. Brazil, Malta, Thailand, Argentina, Latin America, and the Caribbean). Works that are relevant to our work are those by Tapio (2005), Yang et al. (2018), and Yang and Yang (2019).

The contribution of this study is twofold. First, following Tapio (2005) we examine the decoupling effect for the 51 US regions over the period 1990-2017 and, second, we use the methodological framework of Phillips and Sul (2007, 2009) to explore the existence of convergence clubs among U.S. regions estimated decoupling indices over the period from 1990 to 2017. Therefore, the present work fills in the gap in the literature regarding the examination of the decoupling effect in the U.S. geographical region by providing recent evidence of convergence among regions with estimated decoupling indicators.

3. Data description and Methodology

This section describes the methodology we use to examine the convergence analysis developed by Phillips and Sul (2007, 2009) alongside the sample and variable description. The reason for relying on the P-S methodology over other classical convergence analysis (e.g., β and

[7] The framework includes 5 sates, that is, coupling, relative and absolute decoupling, negative decoupling and coupling. The last two states encompass periods in which output declines (negative GDP growth).

σ- convergence methodology) lies in the superiority of the former against the latter as it has been documented by the related literature (see among others Eleftheriou and Polemis, 2020; Clemente et al., 2019 and Apergis et al., 2012).

3.1 Variable description

In our analysis, we use emission and GDP data for the U.S. regions over the period 1990-2017. Specifically, to construct the decoupling indices we utilize one global carbon dioxide-CO_2 and two local nitrogen oxides-NO_X and sulfur dioxide- SO_2 pollutants for the 50 U.S. states and the District of Columbia (DC). Regional GDP has been extracted from the Bureau of Economic Analysis (BEA), is adjusted from inflation, and is measured in millions of 2009 USD. The environmental hazards are measured in metric tons, and they have been extracted from U.S. Energy Information Administration (EIA). Figure 1 presents the distribution and the descriptive statistics of the variables used in our analysis.

[Figure 1 about here]

3.2 Methodological framework

To evaluate the impact of decoupling several studies suggest that the first stage is to perform a decoupling analysis by constructing the decoupling indices-DI (De Freitas and Kaneko, 2011; Moutinho et al., 2018; Yang et al., 2018; Yang and Yang, 2019). The decoupling indices (DI) of the three pollutants can be expressed as:

$$\omega(CO_2, GDP) = \frac{\frac{\Delta CO_2}{CO_2}}{\frac{\Delta GDP}{GDP}},\ \omega(SO_2, GDP) = \frac{\frac{\Delta SO_2}{SO_2}}{\frac{\Delta GDP}{GDP}},\ \omega(NO_X, GDP) = \frac{\frac{\Delta NO_X}{NO_X}}{\frac{\Delta GDP}{GDP}}. \quad (1)$$

The index represents the ratio of the changes of pollutants over the changes in GDP. The obtained value represents the DI for every pollutant. In our analysis, we construct the DIs on a non-overlapping year-by-year basis (i.e. 1990-1991, 1992-1993, 1994-1995,…, 2016-2017). Table 1 presents all possible classifications of the estimated decoupling indices (see Tapio, 2005).

Specifically, we have eight different classifications namely “Expansionary Negative Decoupling”; “Strong Negative Decoupling”; “Weak Negative Decoupling”; “Weak Decoupling”; “Strong Decoupling”; “Recession Decoupling”; “Growing Link” and “Recession Link”. For instance, if among two time periods we obtain $\Delta CO_2>0$, $\Delta GDP>0$, and the DI has a value greater than 1.2, then the state of the region is facing an “*Expansionary Negative Decoupling*” of CO_2 emissions. In another case, if a region among two time periods has $\Delta SO_2<0$, $\Delta GDP>0$, and the DI value less than 0, then the state of the region is facing a “*Strong Decoupling*” of SO_2 emissions. This case occurs when a region increases its GDP growth rate while decreasing its level of SO_2 emissions.

[Table 1 about here]

Furthermore, we utilize Phillips and Sul (2007, 2009) methodological framework, to explore the existence of convergence clubs among U.S. regions estimated decoupling indices over the examined period. The convergence analysis starts by letting first a single factor model be expressed as:

$$\omega_{i,t} = \varphi_{i,t}\lambda_t. \tag{2}$$

The factor $\varphi_i$measures the distance among the systematic part of $\omega_{i,t}$ and the common factor λ_t.It must be noted that both the $\varphi_{i,t}$ and λ_t are time-varying and the behavior of $\varphi_{i,t}$ can be expressed in a semiparametric form as:

$$\varphi_{i,t} = \varphi_i + \sigma_i\vartheta_{i,t}L(t)^{-1}t^{-\alpha}, \tag{3}$$

where $\vartheta_{i,t}$ is $\mathrm{iid}(0,1)$ across i, φ_i is fixed and $L(t)$ represents a varying function having $L(t) \to \infty$ as $t \to \infty$ and $\varphi_{i,t}$convergences to φ_i for all $\alpha \geq 0$. Then $\omega_{i,t}$can be decomposed as:

$$\omega_{i,t} = f_{it} + \alpha_{it}, \tag{4}$$

where f_{it} contains the systematic and α_{it} the transitory components, therefore we can have:

$$\omega_{i,t} = \left(\frac{f_{it}+\alpha_{it}}{\lambda_t}\right)\lambda_t = \varphi_{i,t}\lambda_t, \text{ for all } i \text{ and } t. \quad (5)$$

According to Phillips and Sul (2007), the transition coefficient can be expressed as:

$$\mu_{it} = \frac{\omega_{i,t}}{1/N\sum_{i=1}^{N}\omega_{i,t}} = \frac{\varphi_{i,t}}{1/N\sum_{i=1}^{N}\varphi_{i,t}}, \quad (6)$$

Equation (6) measures the transition coefficient $\varphi_{i,t}$ to the panel average at time t and μ_{it} is called a relative transition parameter. Phillips and Sul (2007, p.1780) explain that μ_{it} has by a definition a cross-sectional mean of unity and when $\varphi_{i,t}$ convergences to φ_i, implies that also μ_{it} convergences to unity. In the latter case the cross-sectional variance of $\varphi_{i,t}(\sigma_t^2)$ convergences to zero in the long run, formally we have that:

$$\sigma_t^2 = \frac{1}{N\sum_{i=1}^{N}(\mu_{it}-1)^2} \rightarrow 0 \text{ as } t \rightarrow 0. \quad (7)$$

As described by Phillips and Sul (2007), we need several steps to perform a regression test for convergence. The t test of the null hypothesis of convergence suggests that:

$\mathcal{H}_0: \varphi_i = \varphi \text{and} \alpha \geq 0$, whereas the alternative suggests $\mathcal{H}_1: \varphi_i \neq \varphi \text{for all } i$ or $\alpha < 0$.

Let the cross-sectional variance ratio M_1/M_t, where:

$$M_t = \frac{1}{N\sum_{i=1}^{N}(\mu_{it}-1)^2}, \mu_{it} = \frac{\omega_{i,t}}{1/N\sum_{i=1}^{N}\omega_{i,t}}. \quad (8)$$

Then by utilizing the following regression we estimate a t statistic $\left(t_{\hat{\beta}}\right)$for $\hat{\beta}$ as:

$$\log(M_1/M_t) - 2\log L(t) = \hat{\alpha} + \hat{\beta}\log t + \hat{u}_t, \text{ for } t = [\rho T], [\rho T]+1, \dots, T \text{ with } \rho > 0. \quad (9)$$

Notice that in regression presented in (9) we use $L(t) = \log(t+1)$, $\hat{\beta} = 2\hat{\alpha}$ and $\rho = 0.3$. Finally, at 5% level, the null hypothesis of convergence is rejected if $t_{\hat{\beta}} < -1.65$. The convergence hypothesis implies that $\mu_{it} \rightarrow 1$ and $M_t \rightarrow 0$ as $t \rightarrow \infty$.

4. Empirical findings

This section presents the empirical results of the study. In the first stage, we present the results of the DIs based on the eight decoupling criteria as suggested by Tapio (2005) generated for the 51 US regions over the period 1990-2017. Then in the second stage, we test for club formulation convergence between the sample regions utilizing the P-S convergence algorithm.

4.1 Evolution of decoupling indicators

Tables 2-4 illustrate the classification of the US regions into eight decoupling regimes as is firstly indicated by Tapio (2005). A careful look at the relevant tables uncovers some interesting remarks. Regarding the CO_2 decoupling indicator, it is evident that nearly 17 US regions (California, Colorado, District Columbia, Delaware, Georgia, Hawaii, Kansas, Maine, North Carolina, New Hampshire, Nevada, Pennsylvania, South Dakota, Tennessee, Texas, Utah, and Washington) have strongly decoupled their CO_2 emissions ("*leaders*") from economic growth since the relevant decoupling indicator/ratio (ω) though negative dictates that the emissions growth rate is negative (numerator) compared to the positive growth rates (denominator).

As it is evident from the relevant table, in these regions, the strong decoupling criterion prevails over the rest seven criteria for the sample period (1990-2017). This translates into significant progress toward tackling climate change at the regional level regardless of federal policy. This could be attributed to several important drivers. First, technological progress alongside the regional environmental policies has allowed some US states to reduce their carbon dioxide emissions in favor of their ecological footprint. Second, other factors including the major shift from "dirty" energy resources (fossil fuels) to "cleaner" ones (natural gas, renewables) especially in the electricity generation sector in tandem with more stringent energy-efficient regulations (e.g., efficiency standards for buildings and vehicles, lighting, and appliances, etc) have also played a key role on enhancing the decoupling effect. Moreover, decarbonization of the electricity sector with the substitution of gas for coal plays also a crucial role in decoupling policy efforts. It is noteworthy that in a few states such as Georgia, North Carolina, and Delaware, the decline in carbon intensity came mostly from improvements in energy efficiency in buildings and industries, and of the implementation of "*green*" policy strategies shifting from heavy manufacturing to less carbon-intensive service sectors (Saha, and Jaeger, 2020). On the other hand, regions such as Rhode Island Louisiana, Idaho, Mississippi, New Jersey, Oregon, and Wisconsin have coupled their carbon dioxide emissions volume from economic growth and thus can be characterized as "*laggards*". These regions can be classified into expansionary negative decoupling or strong negative decoupling regimes.

[Table 2 about here]

Table 3 illustrates the diachronic regime state of the NO_x decoupling indicator. A quick look at the relevant table, reveals some important findings. As it is evident, in this case more US regions have achieved strong decoupling effects from economic growth (Alaska, Colorado, Connecticut, Delaware, Florida, Georgia, Hawaii, Iowa, Illinois, Indiana, Kansas, Massachusetts, Maryland, Michigan, Minnesota, Missouri, North Carolina, Nebraska, New Mexico, Nevada, New York, Ohio, Pennsylvania, South Carolina, South Dakota, Tennessee, Texas, Utah, Virginia, Washington, Wisconsin, West Virginia, and Wyoming). Especially for Georgia, it is interesting to note that the strong decoupling criterion prevails across the whole period compared to the rest US regions that fall within this regime.

[Table 3 about here]

On the contrary, some regions such as Alaska, California, Maine, New Hampshire, and Oregon can be classified into the "*expansionary negative decoupling*" regime, with the relevant ratio ω greater than 1.2 (elasticity). This means that the (positive) NO_x volume growth is much greater than the (positive) level of economic growth. We also note that the rest of the sample regions does not appear to have a consistent regime. Lastly, similar findings occur when we assess the diachronic SO_2 decoupling indicator (see Table 4).

[Table 4 about here]

4.2 Convergence club clustering

The results drawn from the convergence algorithm are illustrated in Table 5. As it is evident, the null hypothesis of convergence cannot be accepted for the full sample (51 US regions) since the t-statistic is smaller than the critical value (-1.65) at a 5% level of statistical significance. The next step is to test for the existence of different convergence clubs drawn from the whole sample for the three pollutants (CO_2, SO_2, and NO_X).

[Table 5 about here]

It can be easily shown that in the case of the CO_2 decoupling indicator, there are four primary convergence clubs (see Table 6, Column 1) consisting of an unequal number of regions. Specifically, Club 1 consists of seven regions (Florida, Indiana, Minnesota, Mississippi, New Jersey, New Mexico, and Vermont). Club 2 has 38 members (Alaska, Alabama, Arizona, California, Colorado, Connecticut, Georgia, Hawaii, Iowa, Illinois, Kansas, Kentucky, Louisiana, Massachusetts, Maryland, Maine, Michigan, Missouri, Montana, North Carolina, North Dakota, Nebraska, New Hampshire, Ohio, Oklahoma, Oregon, Pennsylvania, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Virginia, Washington, Wisconsin, West Virginia, and Wisconsin), while Club 3 consists only of two regions, namely Denver and Nevada. Similarly, Club 4 has also two members (Arkansas and District Columbia). On the contrary, two regions (Idaho and New York) formulate a non-converging group. However, for the formulated clubs, we observe that the estimated logt values are greater than the critical value of -1.65 suggesting the existence of a convergence trend of the decoupling effect among the sample US regions.

[Table 6 about here]

In the case of the SO_2 decoupling indicator, there are three primary convergence clubs (see Table 7). Club 1 is the largest of all consisting of 42 US regions, while Club 2 has four members namely Arkansas, Connecticut, South Dakota, and Wyoming. Club 3 consists only of two regions, (Mississippi and Rhode Island). On the contrary, two regions (District Columbia and New York) formulate a non-converging group.

[Table 7 about here]

On the contrary, based on the NOx decoupling indicator, we identify eleven primary convergence clubs with almost equal size. Based on the estimated values, we cannot reject the null hypothesis of convergence in all the eleven clubs since the t-statistic is larger than the critical value (-1.65) at a 5% level of statistical significance. The two largest primary convergence clubs (Club 3 and Club 4) consist of seven US regions, while the smallest formulated clubs include only two regions (see Club 9, 10, and 11). Moreover, we notice that spatial clustering can be observed in Club 1 which implies commonalities among the regions within this formulated club (see Figure. 2).

[Table 8 about here]

[Figure 2 about here]

Having delineated the convergence clubs based on P-S (2007) generic algorithm, the analysis proceeds with the interpretation of the speed of convergence (α) among the formulated clusters.[8] A deeper inspection of Table 6 reveals some important findings. First, the speed of convergence is positive and varies significantly across the four primary convergence clubs. However, for Club 4 it is reported a negative speed of adjustment equal to α = -1,804. Second, the

[8] Based on Phillips and Sul (2007), the speed of convergence α can be calculated as half the estimated convergence coefficient.

first club, records an absolute value of α = 0,411 approximately, indicating a high adjustment speed to convergence among other clubs. Third, Club 3 is characterized by a small value of convergence speed equal to α = 0,007. This means that the two club regions (Denver and Nevada) are approaching one another more slowly in relative terms. It is noteworthy that this value is almost fourteen times greater than the relevant one that appears in Club 2 (α = 0.11).

Similarly, in the case of the SO_2 decoupling indicator, we observe a positive convergence speed in all the formulated clubs (see Table 7). However, the speed of convergence varies significantly between the three primary detected clubs, with the formulated Club 3 (Mississippi and Rhode Island) recording the highest speed (α = 1,882) and the largest in magnitude Club 1 the lowest (α = 0,589).

This pattern is fully reversed in the case of the NO_x decoupling indicator. As it is evident from Table 8, we argue that except for Club 11, where the convergence speed is negative (α = -0,127), the rest primary clubs have positive convergence speed ranging from 0,074 (Club 7) to 0,892 (Club 9).

We now turn our attention to whether it is possible to merge some of the initial convergence clubs found above. Therefore, we apply the Phillips and Sul (2009) methodology on the different estimated decoupling indicators broken down by the three global (CO_2) and local pollutants (SO_2 and NO_x) respectively. The relevant results are also illustrated in Tables 7-9 (see the fourth column). Regarding the CO_2 decoupling indicator (see Table 6), we notice that we fail to reject the null hypothesis of convergence in two cases (Club 1+2, and Club 2), revealing that the four primary convergence clubs can be finally reduced to three. As it is evident from the relevant table the first two clubs can be merged into one larger (merged) "*entity*" consisting of 45 US states with low estimated convergence speed (α = 0,0105).

Similar findings are evident by examining the SO_2 decoupling indicator (see Table 8). In this case, only the initial convergence Club 1 (Idaho, Vermont, Louisiana, Alaska, Florida, New Jersey, Montana, New Mexico, Oregon, Missouri, Nebraska, Tennessee, West Virginia, Oklahoma, Maryland, Georgia, Utah, Arizona, South Carolina, Hawaii, Indiana, Alabama, Texas, Kansas, Pennsylvania, Michigan, Denver, Massachusetts, Iowa, Maine, Illinois, Wyoming, Washington, North Dakota, California, North Carolina, Ohio, Kentucky, Virginia, Colorado, Nevada, Minnesota, and New Hampshire) and Club 2 (Arkansas, Connecticut, South Dakota, and Wisconsin) can be merged into one and the relevant t-statistic (0.989) is larger than the critical value of -1.65 failing to reject the null hypothesis. On the contrary, the t-statistic (-2.374) in primary Club 3 (Minnesota and Rhode Island) falls outside the acceptance of the null hypothesis region, thus rejecting the convergence hypothesis.

A different picture emerges in the case of the NOx decoupling index. It is obvious that after club-merging, there are seven convergence clubs (i.e., primary clubs 9,10,11, and four merged Clubs 1+2, 3+4, 5+6, and 7+8). Moreover, we reject the null hypothesis of convergence in five cases (Club 1+2, Club 3+4, Club 7+8, Club 9, and Club 11). The existence of seven individual decoupling clubs, in this case, postulates that there is extensive heterogeneity in the sample. This might reflect structural differences either in the regional income level (GDP) or in the environmental policies pursued across the US states (Saha and Jaeger, 2020; Camarero, et al, 2014).

Finally, Figure 3 presents the relative transition paths of the decoupling indicators of the pollutants' volume growth from economic growth over the sample period and across the US regions. From the shape of the relevant curvatures, it is evident that the transition paths illustrated in the relevant figure are in line with the convergence test results. Specifically, the global pollutant

(CO_2 emissions) decoupling indicator (see upper left panel of the figure), tends to converge which is most evident for the most transition period. However, the transition curves of the three primary clubs (Club 1, 2, and 3) begin to widen from the mid-2010s until our latest available year (2017) revealing a slow rate of divergence among them. Similarly, for the NOx decoupling indicator (see bottom left panel of the figure), there is a tendency to converge until 2015, when nearly all the primary clubs begin to diverge. It is worth mentioning that Club 1 consisting of northern US states (Alaska, Minnesota, Rhode Island, and Vermont), can be characterized by significant volatility across the sample period (see the relevant spikes) confirming the rejection of the null (convergence) hypothesis (see Table 8 and Figure 2). For the other local pollutant decoupling indicator (SO_2), there is a clear coherent convergence pattern for all the formulated clubs until 2010 when Club 3 begins to slowly diverge.

<Figure 3 about here>

5. Conclusions

The objective of this study is to examine the convergence patterns of decoupling factors of three environmental hazards (CO_2, SO_2, and NO_X) from economic growth across the U.S. regions over the period 1990-2017. By applying the Phillips and Sul (2007, 2009) methodology, we are able to trace convergence clubs and illustrate their transition paths. Specifically, the generic algorithm rejects the convergence hypothesis for the whole sample, justifying the existence of several formulated convergence clubs among the US regions. The empirical findings further elucidate the existence of two "*large*" spatial clusters concerning the CO_2 and SO_2 decoupling indicators (Club 2 and Club 1 respectively). On the opposite, the other local environmental hazard (NO_X emissions) seems to deviate from the "*concentrated*" spatial pattern, since eleven primary convergence clubs are detected across the US territory. This heterogeneity sheds some light on the future direction of the environmental policy that must be pursued by government officials and regulators to combat climate change and successfully decouple the NO_X emissions from the level of regional economic growth.

However, this study is not free from limitations. One of the most prominent one is that we examine only three global and local air pollutants, only one of them (CO2) is related to global warming and the international climate agreements (e.g., Parris Accord). Therefore, future research could focus on the assessment of all greenhouse gases, to further check and validate the results of this analysis. Lastly, policymakers and government officials should seriously address these issues since the role of decoupling and the (regional/federal) environmental policies to achieve this, is one of the most challenging issues.

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List of Figures and Tables

Figure 1: Descriptive statistics for the sample variables

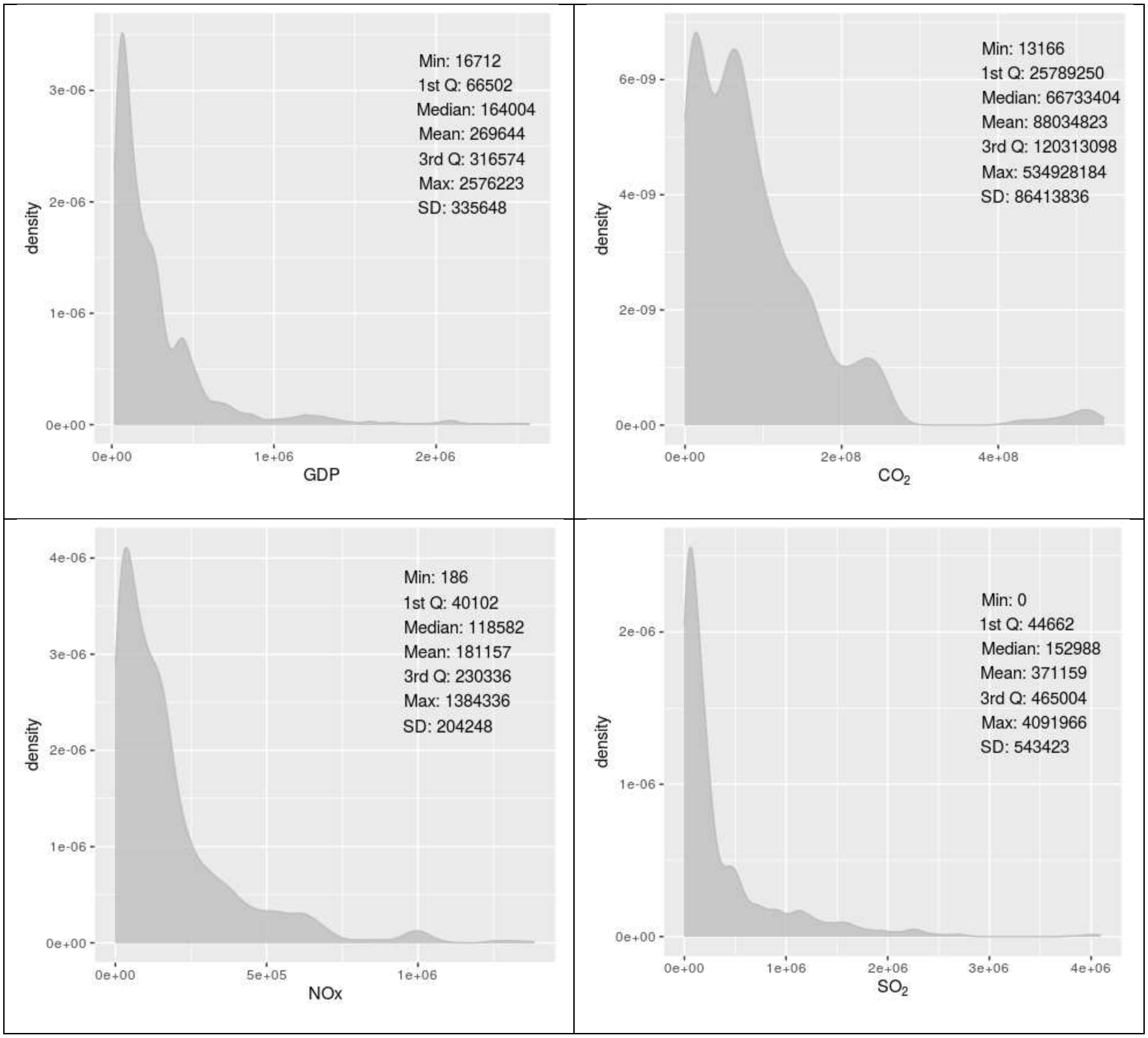
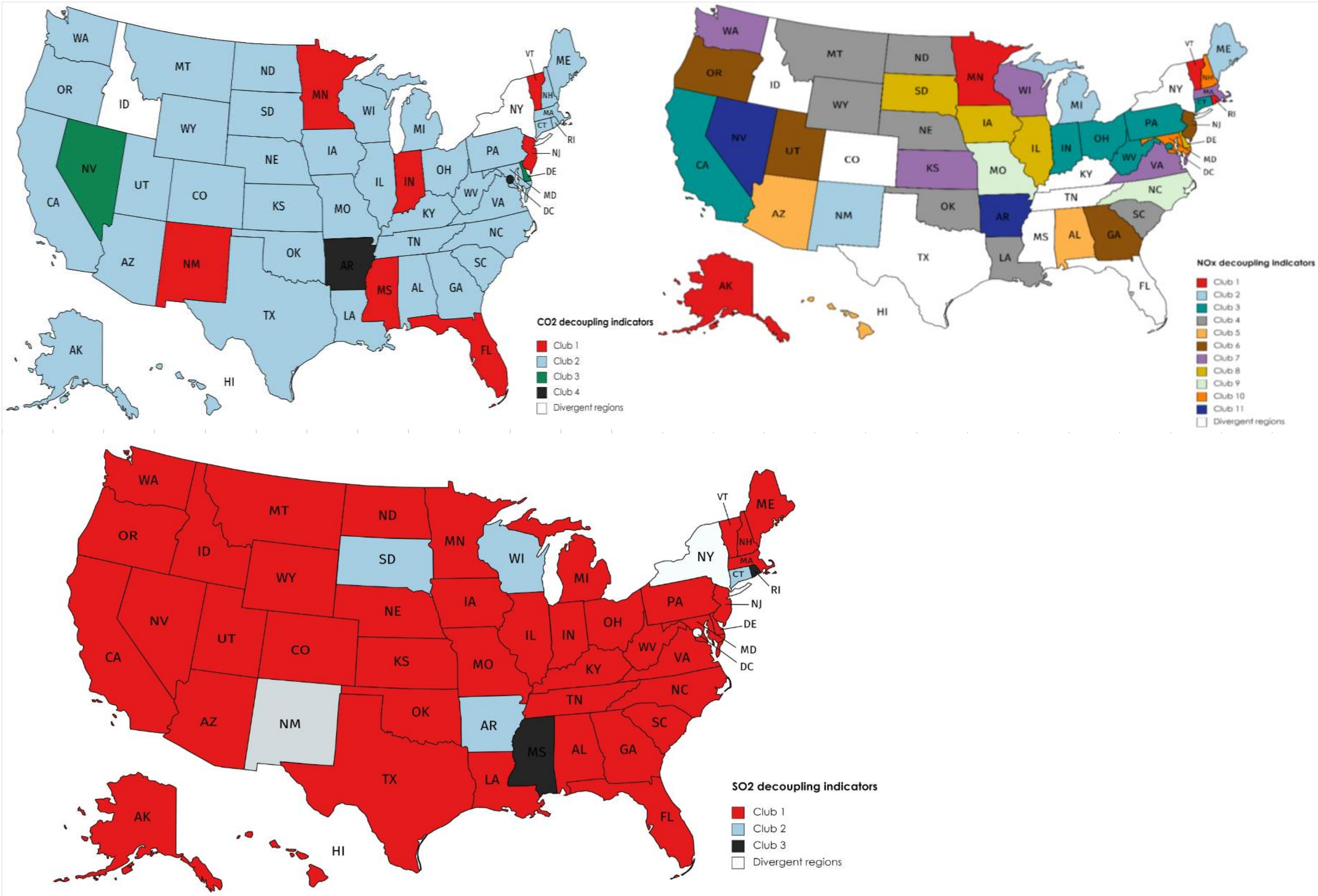


Figure 2: Graphical illustration of primary convergence clubs



Notes: The figure was created with mapchart.net

Figure 3: Transition paths of decoupling indicators per pollutant (CO_2, SO_2 and NO_X)

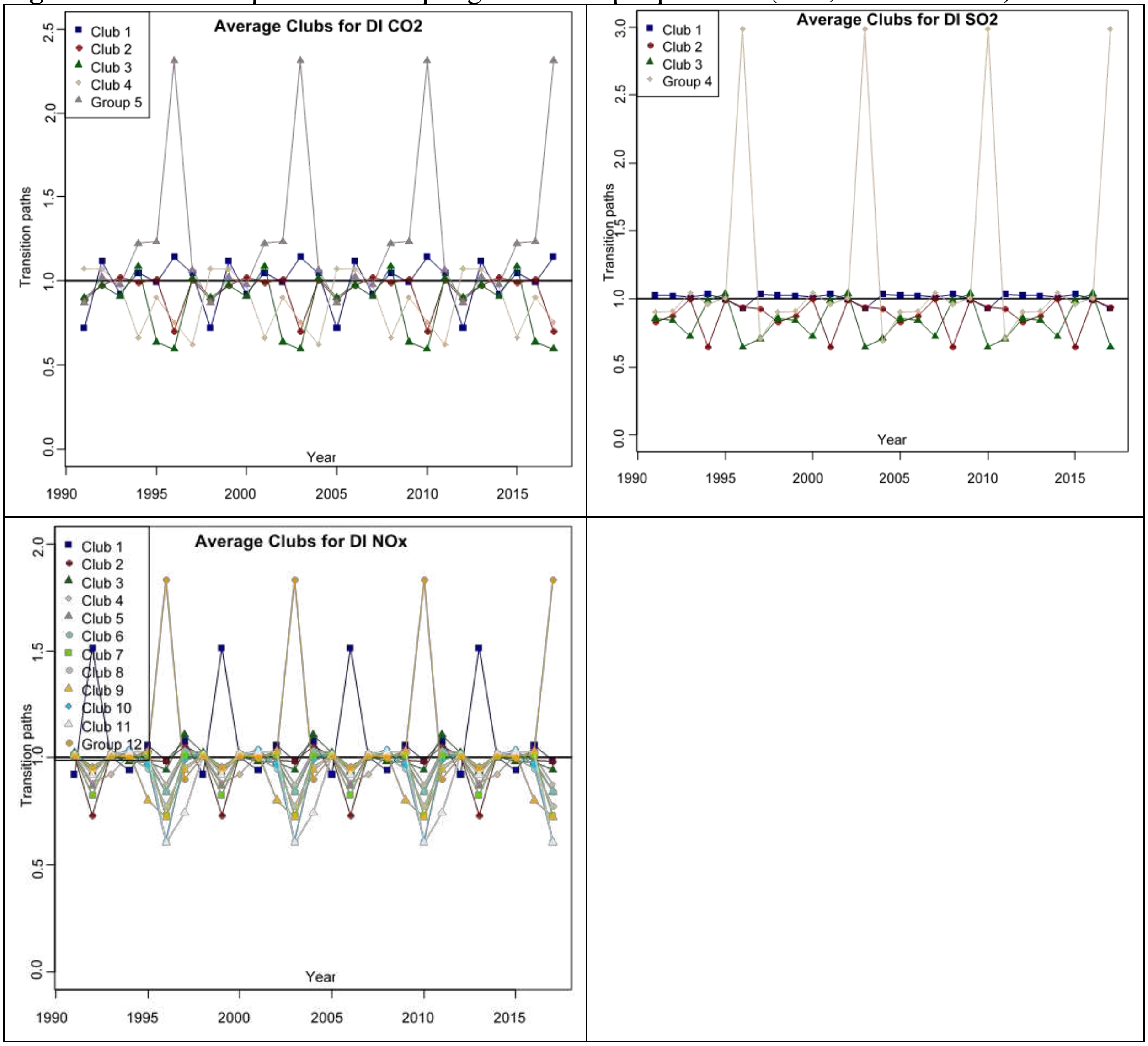


Table 1: Decoupling criteria

Environmental pressures					
CO_2	**NO_X**	**SO_2**	***GDP***	***Decoupling Index-DI***	***Characterization***
$\Delta CO_2>0$	$\Delta NO_X>0$	$\Delta SO_2>0$	$\Delta GDP>0$	$\omega > 1.2$	*Expansionary Negative Decoupling*
$\Delta CO_2>0$	$\Delta NO_X>0$	$\Delta SO_2>0$	$\Delta GDP<0$	$\omega < 0$	*Strong Negative Decoupling*
$\Delta CO_2<0$	$\Delta NO_X<0$	$\Delta SO_2<0$	$\Delta GDP<0$	$0 \leq \omega \leq 0.8$	*Weak Negative Decoupling*
$\Delta CO_2>0$	$\Delta NO_X>0$	$\Delta SO_2>0$	$\Delta GDP>0$	$0 \leq \omega \leq 0.8$	*Weak Decoupling*
$\Delta CO_2<0$	$\Delta NO_X<0$	$\Delta SO_2<0$	$\Delta GDP>0$	$\omega < 0$	*Strong Decoupling*
$\Delta CO_2<0$	$\Delta NO_X<0$	$\Delta SO_2<0$	$\Delta GDP<0$	$\omega > 1.2$	*Recession Decoupling*
$\Delta CO_2>0$	$\Delta NO_X>0$	$\Delta SO_2>0$	$\Delta GDP>0$	$0.8 \leq \omega \leq 1.2$	*Growing Link*
$\Delta CO_2<0$	$\Delta NO_X<0$	$\Delta SO_2<0$	$\Delta GDP<0$	$0.8 \leq \omega \leq 1.2$	*Recession Link*

Source: Tapio (2005)

Table 2: Diachronic count of regions' decoupling state for CO_2 emissions

Regions	Expansionary Negative Decoupling	Strong Negative Decoupling	Weak Negative Decoupling	Weak Decoupling	Strong Decoupling	Recession Decoupling	Growing Link	Recession Link
AK	4	2	2	0	4	2	0	0
AL	6	0	0	4	4	0	0	0
AR	4	2	0	6	2	0	0	0
AZ	4	0	0	4	6	0	0	0
CA	2	0	0	0	8	2	2	0
CO	0	0	0	2	10	0	2	0
CT	4	0	0	0	6	2	0	2
DC	0	0	0	0	10	4	0	0
DE	2	2	0	0	10	0	0	0
FL	4	0	0	2	4	2	2	0
GA	4	0	0	2	8	0	0	0
HI	0	2	0	2	10	0	0	0
IA	6	0	0	2	6	0	0	0
ID	8	0	0	2	2	2	0	0
IL	2	2	0	4	6	0	0	0
IN	0	0	0	6	6	2	0	0
KS	4	0	0	2	8	0	0	0
KY	2	0	0	0	6	0	4	2
LA	0	6	0	6	0	2	0	0
MA	4	2	0	0	6	0	2	0
MD	4	0	2	0	6	0	2	0
ME	4	0	0	0	4	6	0	0
MI	2	4	0	0	8	0	0	0
MN	2	0	0	2	6	2	2	0
MO	4	2	0	2	6	0	0	0
MS	8	0	0	2	2	2	0	0
MT	6	0	0	2	4	0	2	0
NC	4	0	0	0	8	0	2	0
ND	2	4	0	2	6	0	0	0
NE	6	0	0	0	6	0	2	0
NH	4	0	0	0	8	2	0	0
NJ	8	2	0	0	2	2	0	0
NM	4	0	0	4	6	0	0	0
NV	4	2	0	0	8	0	0	0
NY	6	0	0	2	2	4	0	0
OH	4	2	0	2	6	0	0	0
OK	4	0	0	2	6	0	2	0
OR	8	0	0	2	4	0	0	0
PA	0	0	0	4	8	0	2	0

RI	2	6	0	0	6	0	0	0
SC	4	0	0	2	6	0	2	0
SD	6	0	0	0	8	0	0	0
TN	2	0	0	0	10	0	0	2
TX	2	0	0	4	8	0	0	0
UT	2	0	0	2	8	0	2	0
VA	6	2	0	2	4	0	0	0
VT	6	2	0	0	4	2	0	0
WA	4	0	0	0	8	0	2	0
WI	8	0	0	2	4	0	0	0
WV	2	0	0	2	6	2	2	0
WY	0	0	0	6	6	0	0	2

Notes: See Appendix – Table A.1 for the regions' abbreviations.

Table 3: Diachronic count of regions' decoupling state for NOx emissions

Regions	Expansionary Negative Decoupling	Strong Negative Decoupling	Weak Negative Decoupling	Weak Decoupling	Strong Decoupling	Recession Decoupling	Growing Link	Recession Link
AK	6	4	0	0	2	2	0	0
AL	2	0	0	0	12	0	0	0
AR	2	2	0	2	4	0	4	0
AZ	4	0	0	4	6	0	0	0
CA	6	0	0	2	4	2	0	0
CO	0	0	0	2	12	0	0	0
CT	0	0	2	0	10	2	0	0
DC	2	2	0	4	4	2	0	0
DE	2	2	0	2	8	0	0	0
FL	2	0	0	2	8	2	0	0
GA	0	0	0	0	14	0	0	0
HI	0	2	0	2	10	0	0	0
IA	2	0	0	0	12	0	0	0
ID	2	0	0	2	6	2	2	0
IL	0	2	0	0	12	0	0	0
IN	0	0	0	0	12	2	0	0
KS	2	0	0	0	12	0	0	0
KY	4	2	0	2	6	0	0	0
LA	0	4	2	0	4	2	2	0
MA	2	2	0	0	10	0	0	0
MD	0	0	0	2	10	2	0	0
ME	8	2	0	0	0	4	0	0
MI	0	4	0	0	10	0	0	0
MN	2	2	0	0	10	0	0	0
MO	2	2	0	2	8	0	0	0
MS	2	0	0	4	6	2	0	0
MT	4	0	0	2	4	0	4	0
NC	4	0	0	0	10	0	0	0
ND	2	2	0	2	6	2	0	0
NE	2	0	0	2	10	0	0	0
NH	6	0	0	0	6	2	0	0
NJ	2	0	0	0	8	4	0	0
NM	2	0	0	0	10	0	2	0
NV	2	0	0	0	10	2	0	0
NY	2	0	0	0	8	2	0	2
OH	2	2	0	2	8	0	0	0
OK	4	0	0	4	6	0	0	0
OR	8	0	0	0	6	0	0	0
PA	4	0	0	0	10	0	0	0

RI	2	0	2	0	4	4	2	0
SC	2	0	0	2	10	0	0	0
SD	4	0	0	2	8	0	0	0
TN	2	0	0	0	10	2	0	0
TX	4	0	0	0	10	0	0	0
UT	0	0	0	2	12	0	0	0
VA	4	2	0	0	8	0	0	0
VT	4	2	0	0	6	2	0	0
WA	4	0	0	0	10	0	0	0
WI	0	0	0	2	12	0	0	0
WV	2	0	0	0	10	2	0	0
WY	0	2	0	2	10	0	0	0

Notes: See Appendix – Table A.1 for the regions' abbreviations.

Table 4: Diachronic count of regions' decoupling state for SO_2 emissions

Regions	Expansionary Negative Decoupling	Strong Negative Decoupling	Weak Negative Decoupling	Weak Decoupling	Strong Decoupling	Recession Decoupling	Growing Link	Recession Link
AK	4	0	0	2	2	6	0	0
AL	2	0	0	2	10	0	0	0
AR	4	0	2	2	4	0	2	0
AZ	4	0	0	0	10	0	0	0
CA	6	0	0	0	6	2	0	0
CO	0	0	0	2	12	0	0	0
CT	2	0	0	0	8	4	0	0
DC	2	0	0	0	6	4	0	0
DE	2	2	0	0	10	0	0	0
FL	2	0	0	2	8	2	0	0
GA	2	0	0	0	12	0	0	0
HI	2	2	0	6	4	0	0	0
IA	2	0	0	4	8	0	0	0
ID	4	0	0	0	8	2	0	0
IL	0	0	0	0	10	2	2	0
IN	2	0	0	0	8	2	2	0
KS	4	0	0	4	6	0	0	0
KY	4	0	0	0	8	2	0	0
LA	2	2	0	0	4	4	0	2
MA	4	2	0	0	8	0	0	0
MD	4	0	0	0	8	2	0	0
ME	4	2	0	2	2	2	0	2
MI	0	4	0	0	8	0	2	0
MN	2	0	0	0	8	2	2	0
MO	2	0	0	0	10	2	0	0
MS	2	0	0	0	10	2	0	0
MT	8	0	0	4	2	0	0	0
NC	2	0	0	2	10	0	0	0
ND	2	2	0	0	6	2	2	0
NE	4	0	0	4	2	0	4	0
NH	2	2	0	2	8	0	0	0
NJ	6	0	0	0	2	4	2	0
NM	4	0	0	2	8	0	0	0
NV	0	0	0	2	8	2	2	0
NY	4	0	0	0	6	4	0	0
OH	2	2	0	2	8	0	0	0
OK	6	0	0	2	4	0	2	0
OR	8	0	0	0	6	0	0	0
PA	4	0	0	0	10	0	0	0

RI	2	2	0	0	6	4	0	0
SC	0	0	0	2	10	0	2	0
SD	4	0	0	0	8	0	2	0
TN	0	0	0	2	10	2	0	0
TX	2	0	0	2	10	0	0	0
UT	2	0	0	2	10	0	0	0
VA	4	2	0	2	6	0	0	0
VT	6	0	0	0	4	4	0	0
WA	4	0	0	0	10	0	0	0
WI	2	0	0	0	12	0	0	0
WV	4	0	0	0	6	2	2	0
WY	2	2	0	0	10	0	0	0

Notes: See Appendix – Table A.1 for the regions' abbreviations.

Table 5: Convergence clubs for the whole sample per pollutant (CO_2, SO_2 and NO_x)

Category	**log t**	**t-stat**
$\omega(CO_2, GDP)$	-1.364	-17.438*
$\omega(SO_2, GDP)$	-0.680	-7.817*
$\omega(NO_X, GDP)$	-2.042	-16.970*

Notes: The critical value is −1.65, *denotes rejection of the null hypothesis.

Table 6: Convergence clubs for $\omega(CO_2, GDP)$

Category	log t	t-stat	New club	Final classification	log t	t-stat
Club 1 [FL,IN,MN,MS,NJ,NM,VT]	0.823	1.853	1+2	Club 1	0.021	0.413
Club 2 [AK,AL,AZ,CA,CO,CT,GA,HI,IA, IL,KS,KY,LA,MA,MD,ME,MI,MO,MT, NC,ND,NE,NH,OH,OK,OR,PA,RI, SC,SD,TN,TX,UT,VA,WA,WI,WV,WY]	0.220	2.648				
Club 3 [DE,NV]	0.0154	0.108	3	Club 2	-0.002	-0.048
Club 4 [AR,DC]	-3.608	-1.587	4	Club 3	-2.285	-0.942
Divergent [ID,NY]	-2.017	-120.075	-	-	-	-

Table 7: Convergence Clubs for $\omega(SO_2, GDP)$

Category	log t	t-stat	New club	Final classification	log t	t-stat
Club 1 [ID,VT,LA,AK,FL,NJ,MT,NM, OR,MO,NE,TN,WV,OK,MD,GA,UT, AZ,SC,HI,IN,AL,TX,KS,PA,MI,DE,MA,IA,ME,IL, WY,WA,ND,CA,NC,OH,KY,VA,CO,NV,MN,NH]	1.178	9.953	1+2	Club 1	0.989	9.842
Club 2 [AR,CT,SD,WI]	1.865	6.459				
Club 3 [MS,RI]	3.764	3.366	3	Club 2	-2.374	0.099
Divergent [DC,NY]	-2.469	-364.584	-	-	-	-

Table 8: Convergence Clubs for $\omega(NO_X, GDP)$

Category	log t	t-stat	New club	Final classification	log t	t-stat
Club 1 [AK,MN,RI,VT]	1.307	7.649	1+2	Club 1	0.955	6.337
Club 2 [ME,MI,NM]	0.287	1.944				
Club 3 [CA,CT,DC,IN,OH,PA,WV]	0.287	1.430	3+4	Club 2	0.347	2.187
Club 4 [LA,MT,ND,NE,OK,SC,WY]	0.348	1.782				
Club 5 [AL,AZ,HI]	0.738	3.081	5+6	Club 3	0.033	0.248
Club 6 [GA,NJ,OR,UT]	0.550	4.157				
Club 7 [KS,MA,VA,WA,WI]	0.148	1.203	7+8	Club 4	0.405	2.093
Club 8 [DE,IA,IL,SD]	0.374	3.115				
Club 9 [MO,NC]	1.784	2.192	9	Club 5	0.723	4.368
Club 10 [MD,NH]	0.344	1.247	10	Club 6	-0.208	-1.102
Club 11 [AR,NV]	-0.254	-1.142	11	Club 7	0.223	2.158
Divergent [CO,FL,ID,KY,MS,NY,TN,TX]	-3.266	-71.020	-	-	-	-

Appendix

Table A1: Region abbreviations

Region	**Abbreviation**	**Region**	**Abbreviation**
Alabama	AL	Montana	MT
Alaska	AK	Nebraska	NE
Arizona	AZ	Nevada	NV
Arkansas	AR	New Hampshire	NH
California	CA	New Jersey	NJ
Colorado	CO	New Mexico	NM
Connecticut	CT	New York	NY
Delaware	DE	North Carolina	NC
District of Columbia	DC	North Dakota	ND
Florida	FL	Ohio	OH
Georgia	GA	Oklahoma	OK
Hawaii	HI	Oregon	OR
Idaho	ID	Pennsylvania	PA
Illinois	IL	Rhode Island	RI
Indiana	IN	South Carolina	SC
Iowa	IA	South Dakota	SD
Kansas	KS	Tennessee	TN
Kentucky	KY	Texas	TX
Louisiana	LA	Utah	UT
Maine	ME	Vermont	VT
Maryland	MD	Virginia	VA
Massachusetts	MA	Washington	WA
Michigan	MI	West Virginia	WV
Minnesota	MN	Wisconsin	WI
Mississippi	MS	Wyoming	WY
Missouri	MO		