“Economic Uncertainty and the Environmental Kuznets Curve”

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Abstract

The objective of this paper is to examine the impact of economic uncertainty, measured by the Business Confidence Index (BCI), which is closely related to the production decisions of the economy, on the level of CO2 emissions, specifically at the turning point of the Environmental Kuznets Curve (EKC) for 26 countries belonging to the OECD in the period from 1990 to 2020. The specification for the EKC we employ here avoids using nonlinear transformations of potentially nonstationary regressors in panel estimation and it also allows studying the turning point of the EKC. The results we obtained show that the EKC theory for CO2 emissions in the period studied remains valid and that economic uncertainty does not have a significant impact on the EKC turning point. These results vary when using the World Uncertainty Index (WUI), which studies the economy as a whole and not as a specific sector.

Resumen

El objetivo de este trabajo es examinar el impacto de la incertidumbre económica, medida por el Índice de Confianza Empresarial (BCI), que está estrechamente relacionado con las decisiones de producción de la economía, en el nivel de emisiones de CO2, específicamente en el punto de inflexión de la Curva de Kuznets Ambiental (EKC) para 26 países pertenecientes a la OCDE en el período de 1990 a 2020. La especificación para la EKC que empleamos aquí evita el uso de transformaciones no lineales de regresores potencialmente no estacionarios en la estimación por panel y también permite estudiar el punto de inflexión de la EKC. Los resultados que obtuvimos muestran que la teoría de la EKC para las emisiones de CO2 en el período estudiado sigue siendo válida y que la incertidumbre económica no tiene un impacto significativo en el punto de inflexión de la EKC. Estos resultados varían al utilizar el Índice Mundial de Incertidumbre (WUI), que estudia la economía en su conjunto y no como un sector específico.

Keywords — Economic Uncertainty, Environmental Kuznets Curve, CO2 emissions, OECD countries

Bullet Points

- The aim is to estimate the effect that economic uncertainty (from the business sector) has on CO_2 emissions through the Environmental Kuznets Curve (EKC), specifically on the turning point of the EKC.
- To assess the impact of economic uncertainty on the turning point of the EKC, we follow the methodology used by (Leitão, 2010) and (Ridzuan, 2019) that measure the impact of corruption and inequality, respectively, on the turning point, finding significant impacts.
- It is found that the hypothesis of the EKC is confirmed for CO_2 emissions for the period of 1990-2020.
- No significant effect of economic uncertainty (measured through the BCI) on the turning point of the EKC is observed.
- When using the World Uncertainty Index (WUI) as the economic uncertainty variable, a significant and positive effect of economic uncertainty on the turning point of the EKC is found. Therefore, future lines of research are proposed.

Contents

1 Introduction

Climate change, driven by human induced carbon and other greenhouse gases emissions, poses a significant and immediate threat with broad economic implications (Hansen et al. (2023); IPCC (2019); IPCC (2021)). The direct link between carbon emissions and global warming, as outlined in reports like the Intergovernmental Panel on Climate Change (IPCC), leads to extreme weather events, impacting livelihoods and economic resilience globally. Developing countries and vulnerable communities bear a disproportionate burden, worsening existing economic disparities. Job losses, decreased agricultural productivity, and strain on healthcare systems result in lasting economic consequences and human sufferings affecting affect millions of lives (Fortunato et al., 2022) . The escalating frequency of extreme weather events also jeopardizes financial markets and business investments, impacting global economic prosperity (Lancet, 2019). Addressing climate change from a economic standpoint is crucial to mitigate current impacts and promote sustainable development, ensuring equitable distribution of costs and benefits.

Effectively addressing the economic costs involves proactive measures to reduce carbon emissions and control global warming, as emphasized by the IPCC. Urgent action is needed to limit greenhouse gas emissions and avoid long term catastrophic impacts. Implementing policies and technologies for the transition to renewable energy, enhancing energy efficiency, and adopting sustainable practices is crucial (IPCC, 2018). These actions not only help mitigate climate change effects but also create economic opportunities, fostering job creation and innovation (Stern, 2008) . By reducing carbon emissions, we safeguard current well-being and lay the foundation for a more sustainable future.

The intricate relationship between carbon emissions and economic factors has been extensively studied. Economic growth is associated with increased energy consumption and carbon emissions (Stern, 2008). Foreign Direct Investment drives industrial development but can also increase energy use and emissions (Wui, 1999). Advanced financial systems in countries with the capacity to invest in cleaner technologies reduce emissions (Levine, 1997). Environmental practices in industries also influence emissions (Porter and Van Der Linde, 1995). Economic and fiscal policies are crucial; subsidies for fossil fuels may incentivize carbon-intensive use, while pro-renewable policies reduce emissions (Acemoglu et al., 2012) . Economic globalization and trade impact emissions through global supply chains (Davis and Caldeira, 2010). The adoption of clean and renewable technologies contributes to emissions reduction, although their introduction may initially increase emissions (Aghion et al., 2016).

The studies mentioned above are, without a doubt, an contribution to the literature, however, there is a macroeconomic factor that has not yet been explored in detail; economic uncertainty. This is a variable of great relevance to study, especially in times where the world economy is so unstable due to events that occur without warning, such as the COVID-19 pandemic, global financial crises, geopolitical conflicts, natural disasters, etc. Worldwide, political and economic instability has arisen as a result of global uncertainties, which have had a harmful effect on economic activities (Guidolin and la Ferrara (2010); Blattman and Miguel (2010)).

Some studies highlight the concept of economic uncertainty, characterized by a lack of clarity regarding future government policies, particularly in areas such as regulation, monetary and fiscal policy, taxation, and environmental policy (Liu and Zhang, 2022). This uncertainty has repercussions on market volatility, economic activities, and the overall business and household environment.

On the other hand, some empirical studies provide evidence suggesting that environmental conditions initially deteriorate at lower income levels, but subsequently improve as incomes rise. This phenomenon is known as the Environmental Kuznets Curve (EKC) hypothesis. The extensive collection of empirical research on the EKC concept began with the influential study of Grossman and Krueger (1995), in which they identified an inverted U-shaped relationship between per capita income and pollution concentrations for various chemicals.

Understanding the EKC is vital for effective environmental policy design, as it identifies development thresholds where measures are needed to balance economic growth and environmental protection (Stern, 2004). It offers a framework for assessing policy impact on environmental quality (Grossman and Krueger, 1995) and analyzing cost and benefit distribution during a country's development, ensuring equitable implementation (Shafik, 1994) . The EKC emphasizes that economic development and environmental protection are not mutually exclusive, promoting sustainable development (Galeotti et al., 2006).

The turning point in the EKC indicates the level of economic development where the relationship between income and pollution shifts from positive to negative. Recognizing this point aids policymakers in formulating effective strategies, focusing on pollution reduction measures beyond economic growth (Grossman and Krueger, 1991). Analyzing the turning point contributes to the sustainability debate, determining when economic growth becomes environmentally sustainable (Dasgupta et al., 2002). Understanding the turning point enables long-term planning for economic and environmental development, promoting effective natural resource management (Grossman and Krueger, 1991). It also identifies critical factors driving the shift, including cleaner technologies, economic structural changes, and effective environmental policies (Dasgupta et al., 2002).

Given the above, this work seeks to answer the following questions: Does economic uncertainty affect the EKC? More specifically, what is the effect of economic uncertainty on the EKC turning point? The answer to this question could provide important insights into the relationship between economic uncertainty and the environment. If economic uncertainty raises the EKC turning point, it may have a negative impact on the environment. Another important advantage to highlight about this work is that it uses an uncertainty variable, Business Confidence Index (BCI) ,that focuses on the business or production sector of the economy, which is linked to CO2 emissions.

The rest of the paper is organized as follows. Section 2 puts this work in context by presenting the related literature. Section 3 presents the methodology used. Section 4 introduces the variables used in this research, including both the main variables of interest and the control variables. Section 5 presents the estimation methodologies used and the main results. Section 6 presents a robustness exercise of the estimations. Finally, Section 7 concludes.

2 Literature Review

Existing literature characterizes economic uncertainty as the uncertainty arising from government regulations, fiscal policies, monetary policies, taxation, and environmental regulations. These uncertainties can lead to market fluctuations, affecting economic outcomes and the overall environment in which economic agents operate. Researchers, including Handley and Limão (2018), Azzimonti (2018) , Julio and Yook (2016) , and Baker et al. (2016) , have examined the impact of economic uncertainty on the real economy using various proxies. Baker et al. (2016) introduced an Economic Policy Uncertainty (EPU) index based on the frequency of relevant newspaper articles. In the past decade, particularly after the 2007-2008 global financial crisis, studies such as those by Balcilar et al. (2016) and Kang et al. (2020) have demonstrated the negative impact of EPU on GDP and various economic activities, including investment, stock market liquidity, FDI, tourism, and biofuels.

Economic uncertainty also has significant effects on the quality of the environment through various mechanisms or channels. Firstly, the lack of certainty about long-term returns discourages companies from investing in more sustainable technologies, resulting in a lower adoption of environmentally friendly practices (Aghion et al., 2016). Secondly, during periods of uncertainty, governments may loosen environmental regulations to ease economic burdens on businesses, compromising the effectiveness of environmental policies (Millimet and Roy, 2016). Additionally, economic uncertainty can hinder innovation in green technologies, as companies tend to be more reluctant to invest in environmentally sustainable research and development during times of economic volatility (Popp, 2006). Finally, the reduced allocation of government resources during periods of uncertainty could limit funding for essential environmental projects and programs, weakening the government's ability to effectively address environmental challenges (Dasgupta et al., 2002).

2.1 How does economic uncertainty affect the CO2 emissions?

Some scholars have previously examined the relationship between economic uncertainty and CO2 emissions. Nonetheless, the findings have been somewhat inconclusive. The diversity of results can occur mainly because different variables are used as proxies to measure uncertainty, different methodologies are employed, different contaminants are considered, different temporal horizon are contemplated, etc.

Wang et al. (2020) propose two direct consequences of economic uncertainty on CO2 emissions. Elevated levels of uncertainty can limit the consumption of energy intensive goods, resulting in a reduction in CO2 emissions. This diminishing influence of uncertainty on CO2 emissions is denoted as the "consumption effect." Conversely, increased economic uncertainty may lead to a postponement in the investment in renewable and green energy, contributing to an increase in CO2 emissions. The investment in renewable energy involves incurring in higher sunk costs, and enterprises in the renewable energy sector inevitably defer investment when faced with increased economic uncertainty. Undoubtedly, the reduction in investment, especially in the renewable energy sector, has led to an increase in CO2 emissions. This phenomenon is labeled as the "investment effect" (Liu and Zhang, 2022) .

The existing literature can be classified into two main groups. The first line of research suggests that an increase in economic uncertainty leads to a rise in CO2 emissions. This is explained by the negative impact of economic uncertainty on financial conditions, leading industries to prefer traditional, cost-effective, and environmentally harmful energy sources (such as coal and oil), resulting in an increase in CO2 emissions. Amin and Dogan (2021) argue that economic uncertainty has a positive economic effect on CO2 emissions in China. Additionally, Yu et al. (2021) indicate that the level of economic uncertainty at the provincial level in China significantly influences the carbon emission intensity of manufacturing firms. Benlemlih and Yavaş (2023), also show that an increase in economic uncertainty implies an increase in CO2 emissions, at the firm level.

On the other hand, the second line of research argues that economic uncertainty is associated with a reduction in CO2 emissions. Adedoyin and Zakari (2020) investigate the role of economic uncertainty in the complex relationship between energy consumption, the economy, and CO2 emissions in the UK. In their study, they demonstrate that economic uncertainty decreases the level of CO2 emissions in the short term, suggesting that initially, the role of economic uncertainty in CO2 emissions seems to require attention as it acts as a deterrent for emissions. Chen et al. (2021) shows that economic uncertainty has a significant negative impact on per capita CO2 emissions, also showing that this negative effect is greater in countries with emerging markets than in advanced countries.

Finally, it is also relevant to mention studies that suggest that economic uncertainty does not have a significant effect. Raza Abbasi and Fatai Adedoyin (2021) propose that economic uncertainty has an insignificant impact on China's CO2 emissions. Their also studies that show mixed evidence, such as Syed and Bouri (2022), whose results show that economic uncertainty intensifies CO2 emissions in the short term, suggesting that high economic uncertainty is responsible for environmental degradation in the short term. Conversely, in the long term, they conclude that economic uncertainty reduces CO2 emissions, implying that high economic uncertainty improves environmental quality in the long term.

As can be appreciated, the literature is quite varied regarding the impact of economic uncertainty on CO2 emissions, so there is still no clear consensus, and there are opportunities for further research on the topic. Furthermore, few studies have explored the impact of economic uncertainty on CO2 emissions. Most research has primarily focused on the causal relationship between economic uncertainty and CO2 emissions using autoregressive distributional lag models (ARDL) and Granger causality tests.

3 Methodology

To analyze the effect of economic uncertainty on the EKC turning point, we will use the EKC specification developed by Bradford et al. (2005). The main econometric advantage of this specification is that it avoids using nonlinear transformations of potentially nonstationary variables. Additionally, it can be straightforwardly estimated using ordinary least squares (OLS).

The classical expression of the EKC [1] used by Grossman and Krueger (1995) includes logarithmic transformations of per capita income along with its squared and cubed terms as independent variables. When per capita income (or its logarithm) exhibits nonstationary behavior with a unit root, EKC regressions involve nonlinear adjustments applied to these nonstationary predictors, such as squaring and cubing per capita income.

Analyzing regressions with such predictors entails the application of asymptotic theories different from the usual one (Müller-Fürstenberger and Wagner, 2007). As a result, commonly utilized standard panel estimation methods in the field of the EKC, like the fully modified OLS by Phillips and Moon (1999) and the dynamic OLS by Kao and Chiang (2000), are not applicable in this context. Regressions that involve nonlinear transformations of nonstationary processes always overly optimistic about the existence of EKC. An example of the above is shown in Grossman and Krueger (1995) where they found support for the EKC hypothesis for thirteen out of fourteen pollutants. However, Bradford et al. (2005), using the same data, found support only for six out of fourteen pollutants.

It's crucial to acknowledge a significant consideration when applying theBradford et al. (2005) method-

[1] The regression used is as follows:

$$P_{it} = \mu_i + \beta_1 Y_{it} + \beta_2 Y_{it}^2 + \beta_3 Y_{it}^3 + \beta_4 \bar{Y}_{it} + \beta_5 \bar{Y}_{it}^2 + \beta_6 \bar{Y}_{it}^3 + \bar{\beta}' Z_{it} + \lambda t + \varepsilon_{it} \tag{1}$$

where P_{it} is the concentration level of pollution, Y_{it} corresponds to GDP per capita in the station i at the period t and $\bar{Y}_{it}$ is the average income over the three years prior to t . Z_{it} denote other included covariates, λ is the slope of a linear time trend (identical across all stations), and μ_{it} are individual specific effects ology. This approach might lead to an underestimation of the EKC's turning point. For instance, in their study, Bradford et al. (2005) identified a negative turning point for chemical oxygen demand and an exceptionally low turning point for dissolved oxygen, even though there was evidence of the EKC for both pollutants.

Considering this concern, it is advisable not to regard the turning point estimated through Bradford et al. (2005) method as a reliable estimate. Although this is not the ideal scenario, we can continue to examine the EKC hypothesis and the influence of economic uncertainty on the turning point of the EKC, provided we remain mindful of the previously mentioned caveat. Despite what was mentioned above in the research of Ridzuan (2019) and Leitão (2010) it is shown that the results are independent of the approach used both when studying the effect of income inequality and corruption on the EKC respectively.

The EKC model proposed by Bradford et al. (2005) relies on the average per capita income and its average growth rate, placing greater emphasis on long-term changes as opposed to year-to-year income fluctuations. In this model, the relationship between pollution and income is expressed as follows:

$$\frac{\partial P_t}{\partial t} = \alpha(y - y^*)g \tag{2}$$

The equation 2 shows that the change in pollution emissions P depends on the growth rate of income g and the distance between income y to the turning point y^*. If the factor α is negative and the growth rate g is positive, then pollution will rise until it reaches a turning point y^* and begins to decline, supporting the EKC hypothesis. On the other hand, if the growth rate g is negative, the EKC still holds as long as α is negative (Bradford et al., 2005) .

To verify whether economic uncertainty can be a potential determining factor of the EKC turning point, this work follows the methology of Leitão (2010) and Ridzuan (2019) modeling the turning point y^* in the following way:

$$y^* = \delta_1 + \delta_2 I \tag{3}$$

In the equation 3, I denotes the average economic uncertainty over the sample period for each country. In accordance with previous equation, the turning point will vary across nations, contingent on the degree of economic uncertainty. This can be viewed as a significant advantage, as it alleviates the restrictive assumption that the EKC holds uniformly for all countries. In this work, we will be test whether the parameter δ_2 is statistically greater than zero. If this happens, then economic uncertainty increases the turning point of the EKC.

Combining equations 2 and 3, it is obtained the following expression:

$$\frac{\partial P_t}{\partial t} = \alpha(y - (\delta_1 + \delta_2 I))g \tag{4}$$

Integrating equation 4 with respect the time and taking as constants the average income, the average growth rate and the average uncertainty, we obtain:

$$P_t = \mu + \alpha(y - (\delta_1 + \delta_2 I)gt \tag{5}$$

Where μ is a constant of integration. The equation estimated is obtained from 5 by adding the unobserved country-specific effects (μ_i), a vector of additional explanatory variables (Z). The estimated model uses the natural logarithm of per capita pollutant emissions as the dependent variable. Thus, we have:

$$lnP_{it} = \mu_i + \alpha(y_i g_i t) + (-\alpha\delta_1(g_i t)) + (-\alpha\delta_2(I_i g_i t)) + \beta_3 Z_{it} + \epsilon_{it}$$

Putting terms together we finally arrived at :

$$lnP_{it} = \mu_i + \beta_0(y_i g_i t) + \beta_1(g_i t) + \beta_2(I_i g_i t) + \beta_3 Z_{it} + \epsilon_{it} \tag{6}$$

Where $\beta_0 = \alpha$; $\beta_1 = -\alpha\delta_1$;$\beta_2 = -\alpha\delta_2$

The countries are indexed by i ($i = 1, ..., N$) and time by t ($t = 1, ..., T$). From the equation 6 we have that P_{it} is per capita pollutant emissions in country i in period t; y_i is the country specific measure of average real per capita GDP over the sample period; g_i is the country specific average growth rate of real per capita GDP over the sample period [2]; I_i is the country specific average uncertainty over the sample period and Z_{it} is a vector of control variables that is normally included in explaining the variation in pollutant emissions, these variables include are trade openness (Frankel and Rose (2005); Harbaugh et al. (2002)) and urbanization (Farzin and Bond (2006); Cole and Neumayer (2016)).

As mentioned above this alternative formulation of Grossman and Krueger (1995) is not subject to the unsolved problems arising in panel regression with nonlinear transformations of potentially nonstationary regressors, as pointed out by Bradford et al. (2005). Notice that time is already being considered in the first three explanatory variables.

The hypothesis of an inverse U-shaped relationship pollution and income can be checked from 6 by testing the hypothesis $\alpha = \beta_0 < 0$ and the relationship between the country's economic uncertainty and per capita income at the turning point can be checked by testing the parameter $\delta_2 = -\beta_2/\alpha$. Therefore if the EKC exists, $\beta_2 > 0$ will indicate that there is a positive relationship between economic uncertainty and turning point and if $\beta_2 < 0$ the relationship is negative.

[2] Details of like y_i and g_i are calculated are given in the data's section.

4 Data

4.1 Carbon dioxide (CO2)

This study uses CO2 emissions per capita as the dependent variable [3] . The significance of conducting economic studies related to CO2 is underscored by the substantial economic repercussions this gas has on various aspects of society. Some of the main reasons include:

1. Assessment of Economic Impacts of Climate Change: CO2 is one of the major contributors to climate change. Studying its economic effects is essential to understand and quantify the costs associated with rising temperatures, extreme weather events, and environmental degradation. A seminal study in this regard is the ”Stern Review on the Economics of Climate Change” (Stern, 2008) , which evaluates the economic impacts of climate change and emphasizes the urgency of taking action.

2. Emission Mitigation Policies: Policies aimed at reducing CO2 emissions, such as carbon taxes, environmental regulations, and international agreements, have significant economic implications. Studying these policies is critical to assess their effectiveness and economic consequences. Examples of this can be found in research that evaluates the efficacy of mitigation policies, such as the work of Aldy and Stavins (2012) on the economics of climate policies.

3. Investment in Clean Energy and Technologies: The transition to a more sustainable, low-carbon economy is a critical issue. Economic studies can analyze investment in clean technologies, such as renewable energy and energy efficiency, and their impact on job creation and economic growth (IEA,2020) .

4. Value of Ecosystem Services: CO2 and natural ecosystems are related to carbon sequestration and the provision of ecosystem services. Studying the economic value of these services, such as climate regulation and biodiversity conservation, is essential for making informed decisions about natural resource management (TEEB, 2010).

Data for CO2 per capita emissions are taken from the World Development Indicators (WDI) and include a period between 1990 and 2020.

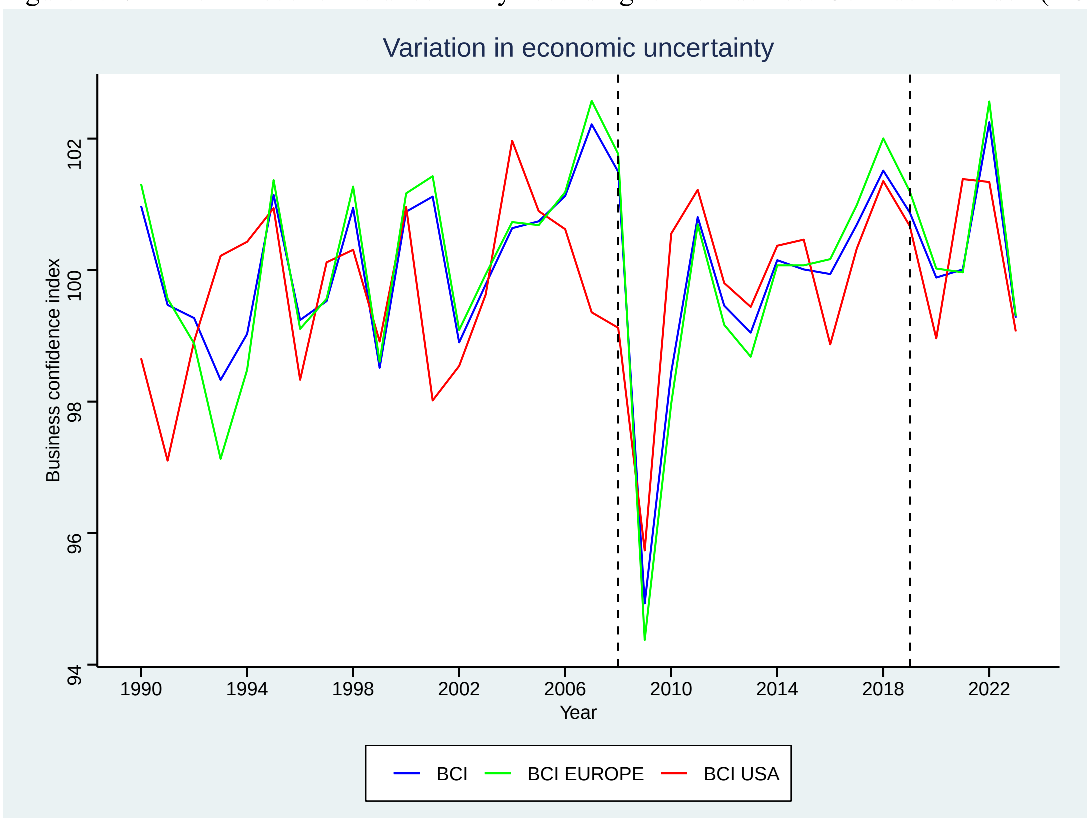
4.2 Economic uncertainty

To measure economic uncertainty, the Business Confidence Index (BCI) is used, which is developed by the OECD. This BCI provides information on future developments, based upon opinion surveys on developments in production, orders and stocks of finished goods in the industry sector. It can be used to

[3] In the appendix, you can observe the correlation among the main variables of this study. It can be appreciated that per capita CO2 emissions positively correlate with per capita GDP. In turn, per capita GDP positively correlates with the BCI, and finally, per capita CO2 emissions negatively correlate with the BCI.

monitor output growth and to anticipate turning points in economic activity. Numbers above 100 suggest an increased confidence in near future business performance, and numbers below 100 indicate pessimism towards future performance. Therefore, the higher this index is, the greater the economic stability and the lesser the economic uncertainty. The main advantage of this uncertainty variable is that it focuses on the production sector of the economy, which, as mentioned above, is closely related to pollution levels as evidenced in Lu et al. (2017).

Figure 1: Variation in economic uncertainty according to the Business Confidence Index (BCI)



At first sight, the economic uncertainty variable used appears to be a good proxy for uncertainty, as there is a noticeable sharp decline in the Business Confidence Index, likely due to the subprime crisis in 2008. It can also be observed that in 2019, there is a decrease due to the Covid-19 pandemic, although not as pronounced as the aforementioned one.

4.3 Other variables

To estimate equation 6 it is necessary to obtain the values for each country of y_i (average of real GDP per capita) and g_i (average of real GDP per capita growth). Real GDP per capita data are used from the WDI, the data are expressed in constant 2010 US dollars. For these calculations it's use the methodology of interpolated income at the sample mid-point used in Bradford et al. (2005).

These values are calculated as follows: Let Y_i^1 be the average real GDP per capita for country i over the period 1990 to 1993, and Y_i^2 be the average real GDP per capita for country i over the period 2017 to 2020. The average growth rate g_i can obtained from $Y_i^2 = Y_i^1 e^{10g_i}$ and the average of real GDP per capita y_i is computed as $y_i = Y_i^1 e^{5g_i}$, where y_i is the interpolated income at the sample mid-point.

Data for control variables,trade openness and urbanization, is obtained from the WDI. Following to Ridzuan (2019) this work uses trade to GDP ratio as a measure for trade openness; and urban population to total population ratio for urbanization. These variables are transformed to logarithms so that their estimated coefficients can be interpreted as elasticities.

Table 1: Descriptive statistics.

Statistic	N	Mean	St. Dev.	Min	Max
BCI	801	100.023	2.17	83.503	109.752
$CO2\ per\ capita$	837	8.570	3.576	2.562	22.015
$Urban$	837	74.053	11.452	47.915	98.079
$Trade$	807	64.455	37.942	13.448	181.345
$GDP\ per\ capita$	820	31,695.05	16,952.19	4,269.7	87,123.66

5 Results

Tables 2 and 3 show the results of two sets of estimations of equation 6 under different specifications, for a sample of 26 countries [4]. These countries belong to the OECD and correspond to high and upper middle income countries according to the ATLAS method, of the World Bank [5]. As discussed in the Section 3, $\beta_0 < 0$ indicates the inverted U-shape of the EKC and β_2 indicates the effect of economic uncertainty on the turning point.

Table 2 shows the estimates obtained using fixed and random effects. Columns one and two are the estimates using fixed effects (without and with controls respectively), while columns three and four are the estimates using random effects (without and with controls respectively). It can be seen that $\beta_0 < 0$ and significant, which confirms the presence of EKC for CO2. In most cases it is also possible to see that $\beta_2 > 0$ and not significant,which indicates that there is no causal effect between economic uncertainty and pollution. Only a positive relationship is shown between both variables, higher BCI (lower economic uncertainty) higher CO2 emissions[6]. In the fourth column (random effects, using controls) it is possible to see that $\beta_2 > 0$ is significant, but only at the 99% level.

Due to the panel structure of the data, it is reasonable to assume that the error terms exhibit heteroskedasticity and autocorrelation. Furthermore, as noted by (Aklin, 2016),it is likely that these errors are not independent across sections, as environmental performance is spatially correlated. To address these issues, this study employs the nonparametric variance-covariance estimator developed by (Driscoll and Kraay, 1998) to adjust standard errors for heteroscedasticity, autocorrelation, and cross-sectional dependence. It's worth noting that while Driscoll & Kraay's estimator is based on large T-asymptotics, it outperforms more commonly used estimators in the presence of cross-sectional dependence, as demonstrated by (Hoechle, 2007).

Table 3 show the estimates through fixed effects and random effects using Driscoll and Kraay estándar errors. It can be seen that the conclusions are similar to those discussed above, the presence of the EKC is confirmed and the uncertainty does not have a significant effect on the turning point. There is only a positive relationship between economic uncertainty and the EKC turning point.

[4]Details of the countries included in the sample in annexes

[5]The World Bank Atlas method - detailed methodology

[6]This can also be interpreted that a higher BCI implies greater confidence about the future on the part of entrepreneurs, which translates into less economic uncertainty.

Table 2: Fixed and random effects models estimation for CO2

	Dependent variable:			
	CO2			
	FE	FE	RE	RE
β_0	$-9.2126\text{e-}06^{***}$	$-1.1123\text{e-}05^{***}$	$-8.9260\text{e-}06^{***}$	$-1.0760\text{e-}05^{***}$
	(7.3336e-07)	(7.6221e-07)	(7.3268e-07)	(7.6068e-07)
β_1	-4.317	-8.495	-5.302	-10.550^{*}
	(5.999)	(6.081)	(5.994)	(6.064)
β_2	0.045	0.087	0.055	0.108^{*}
	(0.060)	(0.061)	(0.060)	(0.061)
$Urban$		0.330^{**}		0.397^{***}
		(0.142)		(0.136)
$Trade$		-0.130^{***}		-0.124^{***}
		(0.034)		(0.033)
$Constant$			2.160^{***}	0.917
			(0.072)	(0.574)
Observations	744	729	744	729
R^2	0.233	0.272	0.218	0.258
Adjusted R^2	0.205	0.243	0.215	0.253
F Statistic	72.536^{***} (df = 3; 717)	52.337^{***} (df = 5; 700)	206.674^{***}	249.244^{***}

Note: FE is fixed effects model and RE is random effects model *p<0.1; **p<0.05; ***p<0.01

Table 3: Fixed and random effects coefficients using the Driscoll and Kraay standard error

	Dependent variable:			
	CO2			
	FE	FE	RE	RE
β_0	$-9.2126\text{e-}06^{**}$	$-1.1123\text{e-}05^{***}$	$-8.9259\text{e-}06^{**}$	$-1.0760\text{e-}05^{***}$
	(4.5695e-06)	(3.5868e-06)	(4.4928e-06)	(3.5313e-06)
β_1	-4.317	-8.495	-5.302	-10.550
	(29.750)	(23.448)	(28.985)	(22.656)
β_2	0.045	0.087	0.055	0.108
	(0.298)	(0.235)	(0.290)	(0.227)
$Urban$		0.330		0.397
		(0.568)		(0.509)
$Trade$		-0.130		-0.124
		(0.100)		(0.085)
$Constant$			2.160^{***}	0.917
			(0.093)	(2.048)

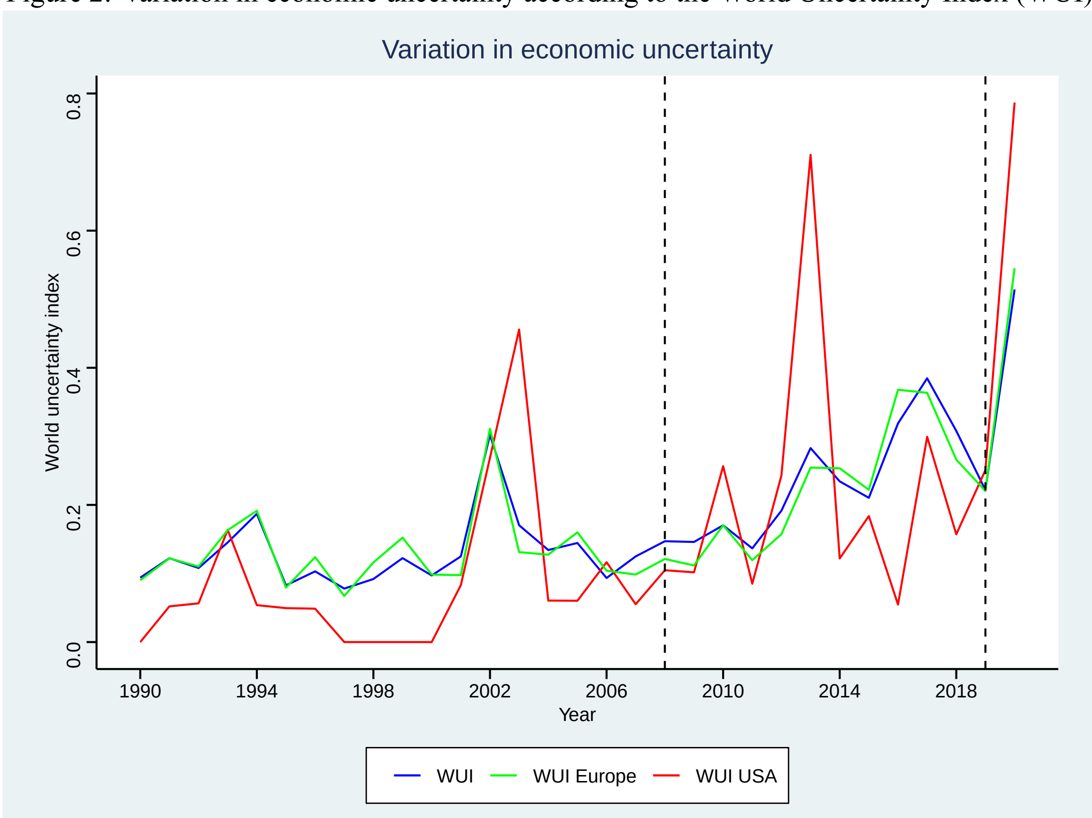
Note: FE is fixed effects model and RE is random effects model *p<0.1; **p<0.05; ***p<0.01

6 Robustness

6.1 World Uncertainty Index (WUI)

Unlike the economic uncertainty variable used previously (BCI), this variable is defined using the frequency of the word “uncertainty” in the quarterly Economist Intelligence Unit country reports (Ahir et al., 2018). So it is expected that the results will different to those obtained using the BCI uncertainty variable, mainly because the latter focuses on the production side of the economy, while the WUI considers the whole economy, and therefore , as was argued in Section 4.2 above, it would deliver less accurate results because it considers both the production side of the economy and the consumption side; and, according to Lu et al. (2017), it is the production side of the economy that is closely related to the pollution levels.

Figure 2: Variation in economic uncertainty according to the World Uncertainty Index (WUI)



It can be appreciated that from 2008 onwards (subprime crisis), there is an increase in economic uncertainty measured through the WUI, and from 2019 onwards, economic uncertainty has increased significantly.

Using the afore mentioned methodology, Table 4 shows estimates using fixed and random effects while the Table 5 shows estimates using fixed and random effects but using Driscoll and Kraay standar errors.

It is important to keep in mind that for this variable the interpretation is somewhat different with respect to the results obtained using the BCI. For this case, if $\beta_2 > 0$, an increase in economic uncertainty implies an increase in the turning point of the EKC. For the estimates where the BCI was used as a variable to measure economic uncertainty, a $\beta_2 > 0$ implied that lower economic uncertainty (greater confidence on the part of entrepreneurs) positively affects the turning point of the EKC. [7]

Table 4 shows that $\beta_0 < 0$ and significant, which confirms the presence of EKC, for estimates made with and without controls, for both fixed and random effects. It can also be seen that $\beta_2 > 0$ and significant. This result implies that when using the WUI as an economic uncertainty variable, an increase in economic uncertainty has a positive and significant impact on the turning point of the EKC. Table 5 shows that using Driscoll and Kraay standar errors the existence of the EKC is confirmed again because $\beta_0 < 0$ and significant, but in this case β_2 is not significant, so there is no evidence indicating that economic uncertainty (measured through the WUI) has an impact on the turning point of the EKC and there is only evidence indicating that there is a positive relationship between economic uncertainty and the EKC turning point.

Table 4: Fixed and random effects models estimation for CO2

	Dependent variable:			
	CO2			
	FE	FE	RE	RE
β_0	$-7.9524\text{e-}06^{***}$	$-1.0124\text{e-}05^{***}$	$-7.7035\text{e-}06^{***}$	$-9.8724\text{e-}06^{***}$
	(7.5072e-07)	(8.2852e-07)	(7.5356e-07)	(8.2828e-07)
β_1	-0.114^{**}	0.087	-0.103^{*}	0.103
	(0.057)	(0.066)	(0.057)	(0.066)
β_2	1.284^{***}	0.719^{***}	1.197^{***}	0.575^{**}
	(0.243)	(0.272)	(0.244)	(0.269)
$Urban$		0.138		0.246^{*}
		(0.151)		(0.143)
$Trade$		-0.112^{***}		-0.112^{***}
		(0.034)		(0.034)
$Constant$			2.158^{***}	1.518^{***}
			(0.068)	(0.589)
Observations	744	729	744	729
R^2	0.261	0.277	0.241	0.258
Adjusted R^2	0.234	0.248	0.238	0.253
F Statistic	84.416^{***} (df = 3; 717)	53.691^{***} (df = 5; 700)	234.534^{***}	249.416^{***}

Note: FE is fixed effects model and RE is random effects model *p<0.1; **p<0.05; ***p<0.01

[7] This difference in interpretation is purely due to the way in which the variables (BCI and WUI) are constructed.

Table 5: Fixed and random effects coefficients using the Driscoll and Kraay standard error

	Dependent variable:			
	CO2			
	FE	FE	RE	RE
β_0	$-7.9524\text{e-}06^{*}$	$-1.0124\text{e-}05^{***}$	$-7.7035\text{e-}06^{*}$	$-9.8724\text{e-}06^{***}$
	(4.0905e-06)	(3.6499e-06)	(4.0445e-06)	(3.6117e-06)
β_1	-0.114	0.087	-0.103	0.103
	(0.295)	(0.288)	(0.292)	(0.283)
β_2	1.284	0.719	1.197	0.575
	(1.152)	(1.123)	(1.141)	(1.094)
$Urban$		0.138		0.246
		(0.446)		(0.401)
$Trade$		-0.112		-0.112
		(0.089)		(0.075)
$Constant$			2.158^{***}	1.518
			(0.091)	(1.671)

Note: FE is fixed effects model and RE is random effects model *p<0.1; **p<0.05; ***p<0.01

7 Conclusions

Several authors had worked on the effect of economic uncertainty on the contamination of the environment, but the evidence provided by them does not allow to arrive at a definitive conclusion because the results of their works vary between positive, negative and even not significant effects, due to the different data use, the different methodologies employed, the different variables used to measure uncertainty, the different temporal horizon taken into considerations, etc.

This work seeks to contribute empirically to clarifying the effect that economic uncertainty has on the EKC turning point, by studying economic uncertainty on the business or entrepreneurial side of the economy through the Business Confidence Index developed by the OECD. This would be an advantage over the existing literature as it focuses on only one sector of the economy. Furthermore, it is important to mention that the majority of existing literature does not focus on the impact of economic uncertainty on CO2 emissions but rather, it primarily examines the causal relationship between these variables using autoregressive distributional lag models (ARDL) and Granger causality tests.

With regard to the results obtained here, it is important to remember that the countries in the sample correspond to high and upper middle income OECD countries according to the ATLAS classification of the World Bank based on the income of the countries, so it is pending for future research and as far as the data allow, to extend the study to lower income countries.

The results obtained show that the presence of EKC is confirmed for the CO_2 emissions. This result is interesting, since it tells us that the EKC theory is still valid, so continuing to study the behavior and the factors that affect it could be essential to combat climate change and environmental deterioration. The estimates also show that economic uncertainty does not have a significant impact on the turning point of the EKC, they only reflect a positive relationship between the BCI and CO_2 emissions (meaning that the higher the BCI or the lower the uncertainty, the greater the CO_2 levels). This tells us that economic uncertainty does not significantly affect the production side of the economy, so it would be interesting for future research to explore the Consumer Confidence Index (CCI), which is also developed by the OECD and focuses on the consumption side of the economy.

When using an alternative variable as a measure of uncertainty such as the WUI, the results are similar. The existence of the EKC for CO_2 is confirmed, but it is also confirmed that economic uncertainty has a positive and significant impact on the turning point of the EKC. This difference in estimates is probably due to how the indicators are constructed (BCI focuses on the production side of the economy, while the WUI considers the economy in general). This may be a motivation to continue studying the EKC and see what other factors affect it, for example, economic uncertainty but now from the consumption side. Other pollutants, such as greenhouse gases (GHGs), CH_4, N_2O, etc., could also be employed to evaluate if the EKC hypothesis is still holding true.

Another important point to highlight for future research is to conduct the study at a more detailed or specific level, such as at the level of a particular country or within a specific region (Liu and Zhang (2022); Raza Abbasi and Fatai Adedoyin (2021); Zhou (2019); Bernard et al. (2015)). Additionally, the study could be extended by focusing on CO_2 emissions at the firm level rather than at the country level. Differences in cultural and ethical perceptions among a variety of countries may influence behaviors in terms of CO_2 emissions, particularly in times of high uncertainty (Benlemlih and Yavaş, 2023).

8 Appendix

8.1 Correlation Between variables

Figure 3: Correlation between BCI and CO2 emissions per capita

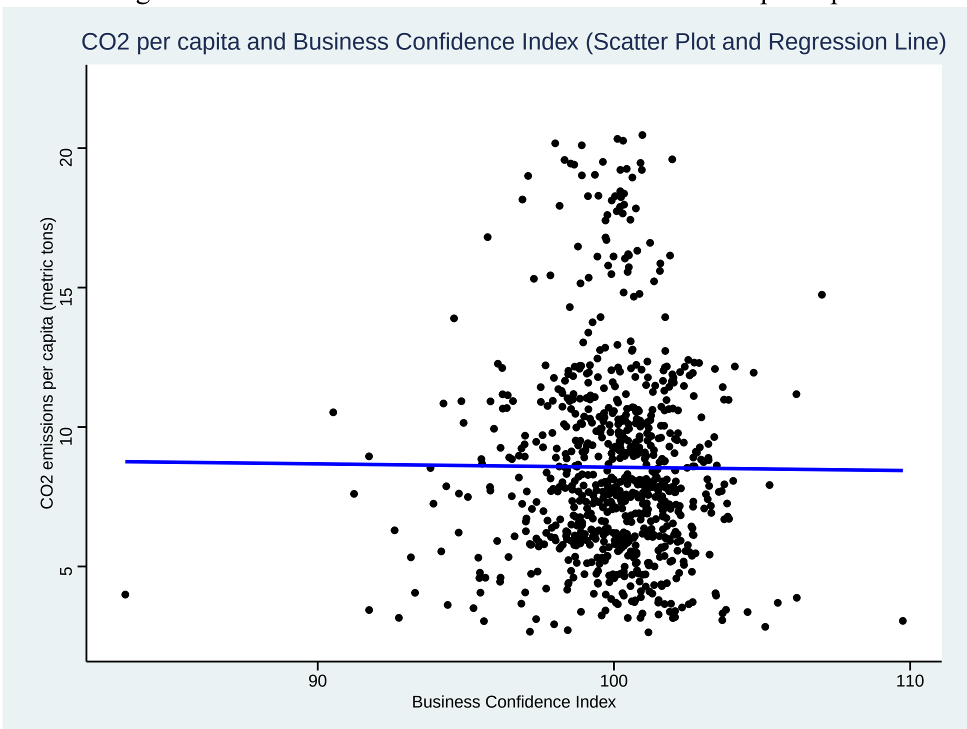


Figure 4: Correlation between BCI and GDP per capita

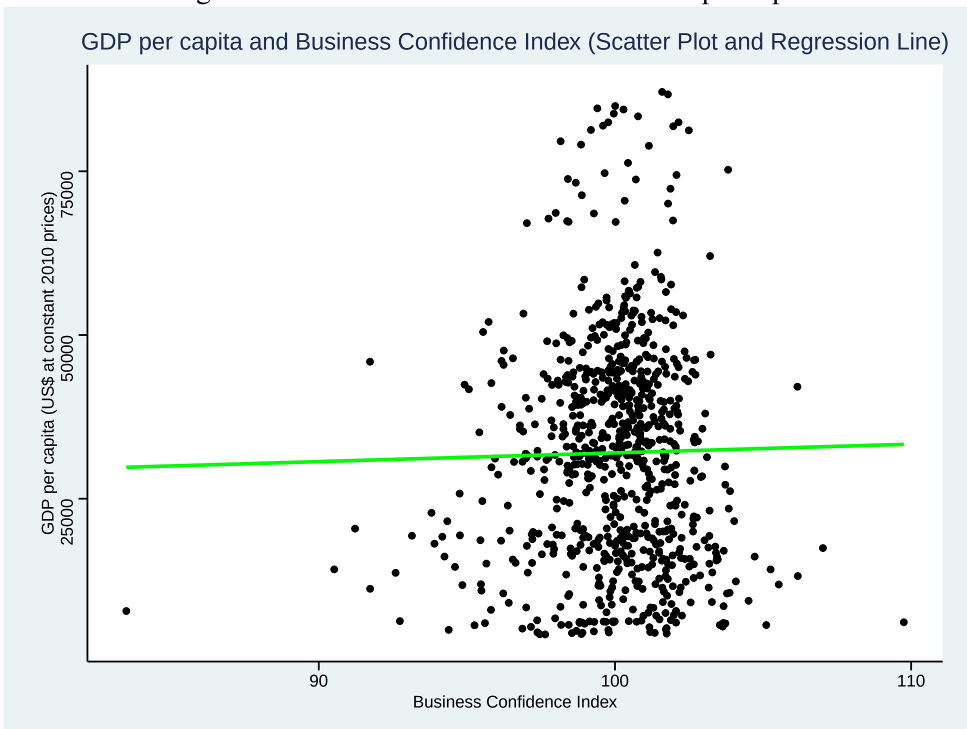
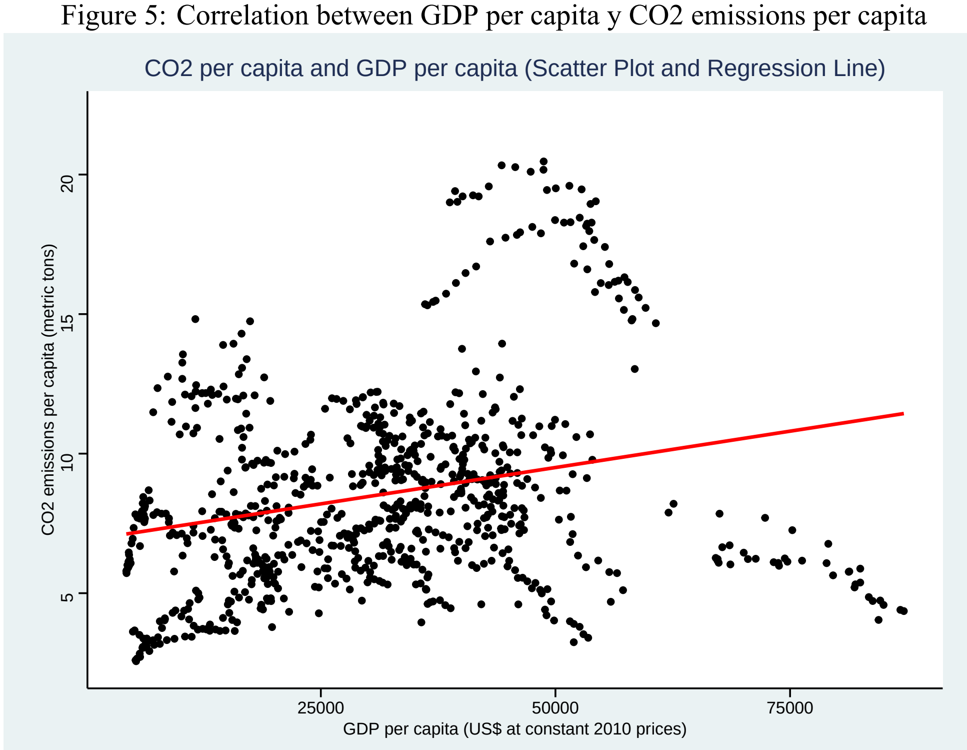


Figure 5: Correlation between GDP per capita y CO2 emissions per capita



8.2 Classification Atlas Method

Table 6: Classification of countries according to the atlas method

Country	Country Code	Atlas Classification
Australia	AUS	High Income
Austria	AUT	High Income
Belgium	BEL	High Income
Switzerland	CHE	High Income
Czech Republic	CZE	Upper Middle Income
Germany	DEU	High Income
Denmark	DKN	High Income
Spain	ESP	High Income
Estonia	EST	Upper Middle Income
Finland	FIN	High Income
France	FRA	High Income
United Kingdom	GBR	High Income
Greece	GRC	High Income
Ireland	IRL	High Income
Italy	ITA	High Income
Japan	JPN	High Income
Latvia	LVA	Upper Middle Income
Netherlands	NLD	High Income
New Zealand	NZL	High Income
Portugal	PRT	Upper Middle Income
Slovak Republic	SVK	Upper Middle Income
Slovenia	SVN	Upper Middle Income
Sweden	SWE	High Income
Turkey	TUR	High Income
United States	USA	High Income
South Africa	ZAF	Upper Middle Income

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