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Economic Development and Industrial Pollution in the Mediterranean Region: A Panel Data Analysis

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Abstract: This paper aims to analyse the determinants of industrial pollution in selected Mediterranean countries. As carbon dioxide (CO_2) emerges as the main pollutant in the industrial sector, per capita CO_2 emissions from manufacturing industries and construction has been taken as a proxy for industrial pollution. The study uses data from the World Development Indicators for the period 1971-2010. The results from the panel data model estimations indicate the existence of an inverse U-shaped relation between GDP per capita and industrial pollution in selected Mediterranean countries, which validates the Environmental Kuznets Curve hypothesis. In addition, the share of industry, per capita energy use, population density and urbanization are found as significant determinants of industrial emissions in the selected countries.

JEL Classification: O13, Q50, Q53

Keywords: economic growth; Environmental Kuznets Curve; industrial pollution; Mediterranean region; panel data analysis

1. Introduction

Over the last several decades, economic growth and the rapid increase in population have raised concerns about the environmental sustainability of current economic systems, and these concerns led to an increase in attention to the determinants of pollution stemming from the main sectors of an economy. Accordingly, various scholars have analyzed the relationship between environmental degradation and economic activity, usually shown by per capita income, and tested the validity of the Environmental Kuznets Curve hypothesis, which is illustrated by an inverse U-shaped relation between pollution and economic development. In general, the use of biochemical oxygen demand as a measure of water pollution and carbon dioxide (CO_2) and sulphur dioxide (SO_2) emissions as measures of air pollution have been widely investigated to proxy environmental degradation.

As the concerns and questions about environmental sustainability grow louder, understanding the determinants of pollution becomes increasingly important, as such detection would make it easier to design and implement appropriate policies against pollution and environmental degradation. Industry, as a highly energy-intensive sector, emerges as a sector that is significantly responsible for carbon emissions, where industry is responsible for more than 30 percent of energy use and 20 percent of total carbon emissions. According to a report by the Blacksmith Institute (2012), the health impact of industrial pollutants is almost equal to or higher than some of the worst global diseases, including malaria and tuberculosis. Industrial pollution depends on several factors, including production technology, quality of inputs, lack of purification equipments, weak environmental regulations and lack of social concern for environmental protection. In this context, determining the responsible factors of carbon emissions in the industrial sector becomes a crucial topic.

This paper aims to analyse the determinants of carbon emissions stemming from the industrial sectors in selected Mediterranean countries. Section 2 overviews the relevant literature regarding the economic growth-environmental pressure relationship, having a glance at Environmental Kuznets Curve studies. Section 3 explains why a focus on carbon emissions in the industrial sector is important and why the Mediterranean region is worth examining in that context. Section 4 explains the structure and the results of the model explaining the determinants of industrial pollution in the selected countries. Finally, Section 5 concludes.

2. Economic Development and Pollution: A Brief Literature Survey

The relation between economic development and environment and the biophysical constraints to economic growth have been a topic of interest in the literature since the publication of *The Limits to Growth* commissioned by the Club of Rome (Meadows et al., 1972). Since then, the accelerating pace of environmental degradation and the alerting effects of climate change enriched the literature on the determinants of pollution and the possible ways to cope with those problems.

The most accredited approach for explaining the linkage of environment and economic development has been the Environmental Kuznets Curve (EKC) hypothesis, which presumes an inverted U-shaped relationship between selected pollution indicators and per capita income, following the original Kuznets Curve approach that postulates a similar relationship between income inequality and per capita income (Kuznets and Simon, 1955). In other words, the EKC hypothesis assumes that as an economy experiences growth in terms of per capita income, the emission level grows in the initial stages, reaches a peak level and then starts declining after a threshold level of per capita income has been reached.

Grossman and Krueger (1991) is cited as the first study to examine this relationship and numerous theoretical and empirical studies followed them in investigating the linkage between economic development and various indicators of pollution. Shafik and Bandyopadhyay (1992), Panayotou (1993), Shafik (1994), Selden and Song (1995), Grossman and Krueger (1995) and McConnell (1997) found empirical evidence in favour of the EKC. However, there are also various studies, like Holtz-Eakin and Selden (1995), Cole et al. (1997) and Stern (2004) that reject the existence of the EKC hypothesis and propose different relationships between environmental damage and per capita income. For example, Stern (1998) argues that the evidence on the inverted-U relationship is only valid for a limited subset of environmental measures and that other pollution problems increase through the existing income range.

When the factors that are responsible for shaping the relationship between economic growth and environmental quality are examined, the literature shows that it is possible to aggregate various factors under five headings (see Dinda, 2004).

The first one is income elasticity of environmental quality demand; when spending on clean environment is assumed as a luxury good that has high income elasticity, the demand for environmental amenities increases as the welfare of consumers rises.

The second factor is scale, technological and composition effects; following Grossman and Krueger (1991), although economic growth leads to environmental degradation through a scale effect in the initial stages and the change in the composition of the economy from agriculture to industry, technological effect through the use and replacement of new and cleaner technology and another composition effect from industry to services and knowledge-based sectors are expected to improve environmental quality (Vukina et al., 1999).

The effect of the liberalisation of international trade and investment flows is referred to as another factor that links economic growth and environmental damage. On one hand, free trade can be beneficial for the environment by raising the wealth of people in developing countries and leading them to demand a cleaner environment (Antweiler et al., 2001); but on the other hand, it is also capable of creating 'pollution havens' as production of certain goods and foreign direct investment shift to countries that have low production costs due to low environmental standards, which would create a 'race to the bottom' (Wheeler, 2000). However, according to Dasgupta et al. (2002), in time, multinational companies respond to investor and consumer pressure in their home countries and tend to raise environmental standards in the countries in which they invest.

Another factor that is argued to create a linkage between economic growth and environmental quality is the self-regulatory market mechanism. Market mechanism is expected to form that relationship through several channels; for instance through the rise in the prices of natural resources as their stocks decrease, where higher prices of natural resources would lead to a shift toward less resource-intensive technologies (Torras and Boyce, 1998). However, according to Hettige et al. (2000), higher energy prices also induce shifts from capital- and energy-intensive production methods to more labour- and material-intensive techniques and these shifts are expected to lead to more pollution.

Finally, the effect of regulations is analysed as a factor shaping the EKC, where it is argued that economic growth leads to the advance of social institutions and environmental regulations (Dasgupta et al., 2001) and also strengthens private property rights. According to Cropper and Griffiths (1994), proper allocation of property rights leads to efficient resource allocation, which helps to increase income and decrease environmental problems. For example, Hettige et al. (2000) argue that the main factor behind the improvement in water quality with increases in per capita income is stricter environmental regulation.

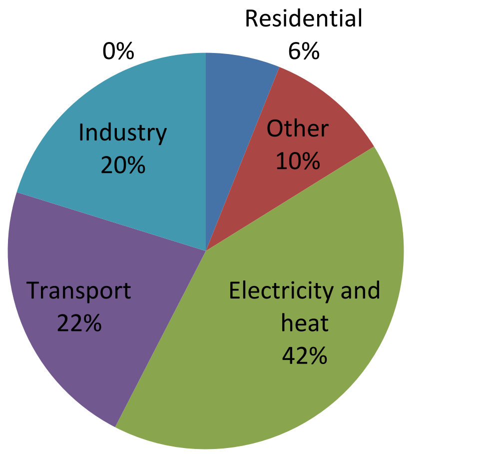
In short, recent work has shown that an inverted-U shaped relationship between economic development and pollution can be derived using a variety of modelling techniques and assumptions, where structural change, technological advances and more effective regulation can also be regarded as potentially important sources of change in pollution (Hettige et al., 2000).

3. Trends in Industrial CO_2 Emissions in the Mediterranean Region

3.1. Industry and pollution

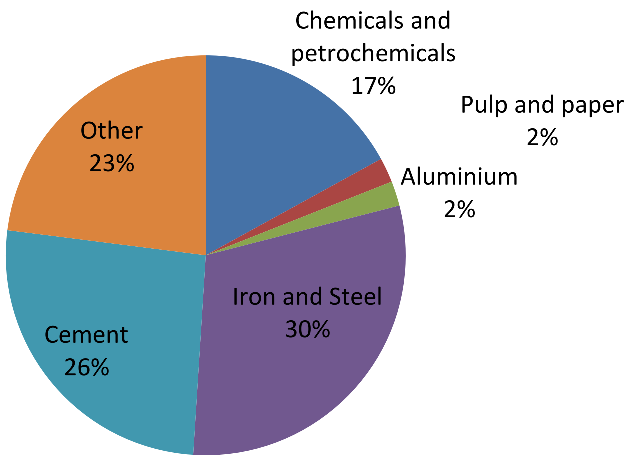
Industry is a highly energy-intensive sector constituting nearly one-third of global energy demand, and 20 percent of worldwide CO_2 emissions are attributable to industrial activities (IEA, 2012) as shown in Figure 1. Both energy demand and carbon emissions from industry are expected to rise in the forthcoming decades. ExxonMobil (2013) expects the industrial demand for energy, including electricity, to grow by about 30 percent from 2010 to 2040, where about 90 percent of the increase in industrial energy demand will come from manufacturing and chemicals. This is expected to lead to significant increases in the emissions from this sector. According to IEA (2010), without widespread deployment of carbon capture and storage technologies, total direct and indirect emissions from industry are expected to rise between 2007 and 2050 by 74% to 91%. As shown in Figure 2, carbon emissions from industry are dominated by the production of goods in iron and steel, cement and chemicals and petrochemicals.

Figure 1: World CO_2 emissions by sector (2010)



Source: IEA (2012, p. 9)

Figure 2: Total direct CO_2 emissions from industry (2007)



Source: Brown et al. (2012, p. 4)

Fossil fuels currently constitute 70% of the total final energy used in industry and as Brown et al. (2012) stress, the options for replacing fossil fuels or switching to less carbon intensive fossil fuels are limited by currently available technologies. According to the forecasts of the

IEA (2010), fossil fuels are expected to remain the predominant source of energy in industry even in the year 2050.

3.2. Industrial pollution in the Mediterranean region

The focus of this paper is on industrial pollution in the Mediterranean region and it aims to capture the determinants of industrial pollution in selected countries of the Mediterranean region.[1]

Evidently, the countries examined are heterogeneous in development level, size and population, but the common feature is that, although the share of industry value added in their GDP falls throughout the years, the size of the industrial sector in terms of value added in constant USD is still high and in most cases has been on a constant rise after the 1980s, especially in the developing countries of the region.

Similarly to all parts of the world with a high level of economic activity and large population, industrial pollution has become increasingly alarming in the Mediterranean region. The environment of the region is one of the richest in terms of biodiversity, but also one of the most vulnerable in the world in the sense that the Mediterranean Sea and its coasts are the source for many of the resources harvested in the region, an important hub for global trade, and also the sink for the negative environmental impacts of these economic activities. These characteristics, combined with the political complexity of the region, imply that the management and protection of the coastal and marine environment will require multilateral environmental agreements and regulations, abided by at a supranational level (UNEP/MAP, 2012).

[1] Albania, Algeria, Cyprus, Egypt, France, Greece, Italy, Lebanon, Malta, Morocco, Spain, Syria, Tunisia and Turkey.

Environmental degradation in the Mediterranean region has been placed in the political agenda since the mid-1970s, where the Barcelona Convention for the Protection of the Mediterranean Sea against Pollution was amended in 1976. This Convention was extended to include coastal areas in 1995 and in the same year a Mediterranean Commission on Sustainable Development was created. As a part of the European Neighbourhood Policy, the European Commission published a Commission Communication establishing an environmental strategy for the Mediterranean and outlined the aims of the strategy as; reducing pollution levels across the region, promoting sustainable use of the sea and its coastline, encouraging neighbouring countries to cooperate on environmental issues, assisting partner countries in developing effective institutions and policies to protect the environment, and involving NGOs and the public in environmental decisions affecting them (European Commission, 2006).

Future trends in Mediterranean coastal areas raise questions and concerns. Transport, tourism and industrial infrastructures are concentrated on the coastal areas of the region, and it is expected that by 2025 coastal urban populations will increase by 20 million, tourist flows will double, and nearly 50 percent of the coastline will be built-up versus 40 percent in 2000 (Benoit and Comeau, 2006). Excessive coastal population and urbanization, combined with increasing demand for industrial production, make the region vulnerable to environmental and social risks.

When the selected countries of the Mediterranean region are analyzed, it is observed that, except for two countries (Albania and Tunisia), the share of carbon emissions from manufacturing industries and construction in total carbon emissions is below the global level.

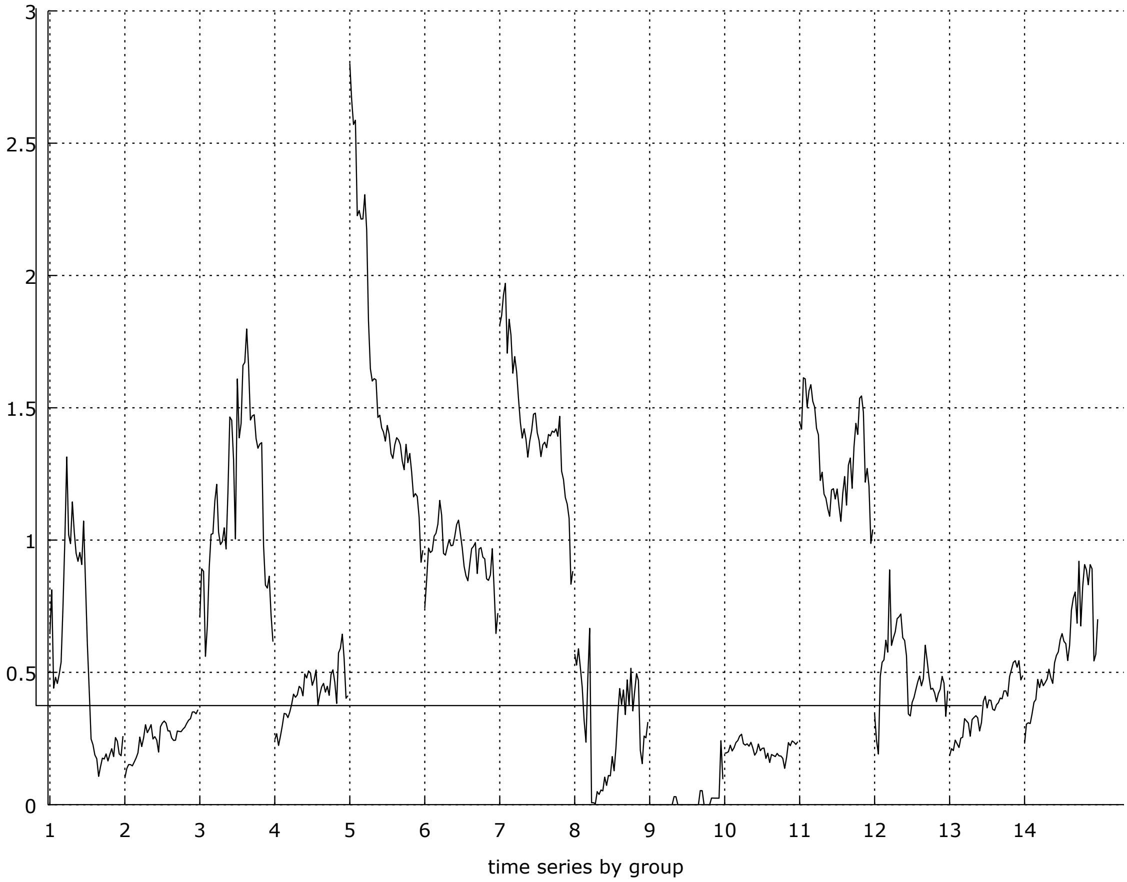
Table 1: Share of CO_2 emissions from manufacturing industries and construction in total CO_2 emissions (%) (2009)

Albania	19.62
Algeria	9.89
Cyprus	9.51
Egypt	14.83
France	16.32
Greece	7.69
Italy	12.51
Lebanon	5.06
Malta	4.00
Morocco	14.75
Spain	15.73
Syria	10.24
Tunisia	19.56
Turkey	14.69
World	*18.18*

Source: Authors' own calculation from WDI (2013)

Figure 3 below shows per capita carbon emissions from manufacturing industries and construction for the selected Mediterranean countries. Among 14 countries, Albania and Cyprus experienced sharp falls in the last three decades. It is observed that the more industrialized countries of the region, France, Italy and Spain, also experienced decreasing trends, especially in the last decade. These three also demonstrated the highest levels of per capita industrial emissions, especially in the beginning of the 1970s. On the other hand, albeit experiencing temporary decreases, Algeria, Tunisia and Turkey have generally seen upward trends in per capita carbon emissions from manufacturing industries and construction. Morocco and Egypt have had relatively low level of emissions compared to the other Mediterranean countries, and have not shown fluctuating figures either. Some countries like Greece and Lebanon have displayed more fluctuating trends in industrial emissions during the investigated period.

Figure 3: Per capita industrial CO_2 emissions in the Mediterranean countries (2010)



Note: 1- Albania, 2- Algeria, 3- Cyprus, 4- Egypt, 5- France, 6- Greece, 7- Italy, 8- Lebanon, 9- Malta, 10- Morocco, 11- Spain, 12- Syria, 13- Tunisia, and 14- Turkey

4. A Panel Analysis of Industrial CO_2 Emissions in the Mediterranean Region

4.1. The model

This paper investigates the evolution of per capita industrial CO_2 emissions in the selected 14 Mediterranean countries and the factors that determine it through the years 1971-2010 by conducting panel data analysis. The countries included in the analysis are Albania, Algeria, Cyprus, Egypt, France, Greece, Italy, Lebanon, Malta, Morocco, Spain, Syria, Tunisia and Turkey. Other Mediterranean countries such as Israel and Libya had to be left out of the analysis due to the lack of data for some necessary variables.

The analysis focuses on two issues; one is to explore whether an EKC relationship exists for the countries of the region during the selected time period and the other is to search for the possible determinants of per capita industrial CO_2 emissions.

First, the EKC relationship is tested using the following standard specification:

$$y_{it} = \beta_0 + \beta_1 x_{it} + \beta_2 x_{it}^2 + \beta_3 x_{it}^3 + \varepsilon_{it} \qquad (1)$$

Here the dependent variable is *indCO2pc*, i.e. per capita industrial CO_2 emissions (in metric tons), which are composed of CO_2 emissions from manufacturing industries and construction containing emissions from combustion of fuels in industry (extracted from WDI, 2013). On the other hand, x_{it} corresponds to *lngdppc*, which is taken as the natural logarithm of PPP-converted GDP per capita at 2005 constant prices (extracted from Penn World Tables, 2012). The existence of second and third exponents of income in the regression equation enables us to test for various forms of environmental pressure - income relationships. For instance, if we end up with $\beta_1 = \beta_2 = \beta_3 = 0$, that means there is no relationship between environmental pollution and income. On the other hand, the case where the coefficients appear to be such that $\beta_1 > 0$, $\beta_2 < 0$ and $\beta_3 = 0$ coincides with an inverted-U shaped figure, namely the EKC relationship. Other potential outcomes for coefficient estimates of income might result in N-shaped, S-shaped or U-shaped figures as well as monotonic increasing or decreasing relationships.

In the second set of analyses, an array of economic indicators is added to income per capita variables in order to offer an explanation for per capita industrial CO_2 emissions. The model is as follows:

$$y_{it} = \beta_0 + \beta_1 x_{it} + \beta_2 x_{it}^2 + \beta_3 x_{it}^3 + \beta_4 Z_{it} + \varepsilon_{it} \qquad (2)$$

where Z_{it} is composed of the following set of variables:

industry: Industry, value added (% of GDP)

urban: Urban population (% of total)

popdens: Population density (people per sq. km of land area)

trade: Trade (% of GDP)

energyuse: Energy use (kg of oil equivalent per capita)

All variables are taken from the World Development Indicators (World Bank, 2013) and used in levels except *lngdppc*.[2] Income per capita date from Penn World Tables is logged in order to avoid extreme positive skewness.

Industry value added share of total output is used with the aim of revealing the economic structure of domestic economies. According to the World Bank (2013) definitions, industry corresponds to "*ISIC divisions 10-45 and includes manufacturing (ISIC divisions 15-37). It comprises value added in mining, manufacturing (also reported as a separate subgroup),*

[2] Summary statistics and correlation matrix for the variables are displayed in Appendices A and B.

construction, electricity, water, and gas." As such, we intend to account for all the polluting and non-polluting industries of each economy in determining the impact on CO_2 emissions.

Urban share of population is a potential factor for increasing industrial emissions. Again according to the World Bank (2013), "*urban population refers to people living in urban areas as defined by national statistical offices. It is calculated using World Bank population estimates and urban ratios from the United Nations World Urbanization Prospects*." As more people live in urban areas either due to increased population or migration from rural to urban, it is expected that more industrial activities will take place in the urban, possibly generating more pollution. Another population measure that is utilised in this paper is population density, which is defined as "*the midyear population divided by land area in square kilometres*" (World Bank, 2013). Countries with higher population density are expected to suffer more from industrial emissions owing to the fact that much denser economic activity takes place in more populated areas.

Trade is another indicator that is expected to be influential on industrial emissions, since most industrial production is feasible thanks to imports and exports of various goods. If industries import polluting inputs (raw materials, intermediate goods, etc.) in order to employ during their production processes, this has a direct or indirect impact on the amount of CO_2 emissions. Besides, if industries are mainly export-oriented and produce polluting goods to sell abroad, the consequences are again unfavourable for the domestic environment. Needless to say, what matters is the structural composition as well as the production technology (whether environmentally-friendly or not) of both imports and exports of a country.

Finally, varying levels of per capita energy use is expected to bear different outcomes in terms of industrial emissions. It would be even more appropriate to examine what sources of energy are utilized and which sectors use more energy. However, due to a lack of detailed statistics for the region, this study relies upon per capita energy use in general for each country. Energy use is defined as "*the use of primary energy before transformation to other end-use fuels, which is equal to indigenous production plus imports and stock changes, minus exports and fuels supplied to ships and aircraft engaged in international transport*" by the World Bank (2013) and is expected to cause higher emissions per capita in countries where primary energy is excessively used. Different uses ranging from residential and commercial to transport and industrial purposes are included under the same heading.

Panel fixed-effects estimations are employed for both model specifications. The reason why fixed effects are preferred to another sort of estimation is that it allows for endogeneity of all the regressors with these individual effects.[3] On the contrary, for instance, when random effects models are considered, all the regressors are assumed to be exogenous with random individual effects, which, usually is not the case (Baltagi, 2005: 19). In our models, as well, there is a potential of endogeneity among some variables, such as population density and industrial emissions. We aim at looking at the effect of population on CO_2 emissions, whereas the causal link from emissions to population density is also a possible one. People might prefer to live in places where industrial pollution is not a serious threat. Hence, we are content with fixed effects estimations which permit such a possibility. Besides, all the models consider time fixed effects and robust standard errors against heteroskedasticity. We choose the "heteroskedasticity and autocorrelation consistent" (HAC) approach suggested by Arellano (2003) to arrive at asymptotically valid estimates of the covariance matrix in the case of both heteroskedasticity and autocorrelation of the error process.

[3] The choice between the fixed- and random-effects estimators is further explored by Mundlak (1978).

4.2. Empirical results

In Model 1 and 2, we test the EKC hypothesis via a third degree polynomial function of income per capita (in natural logs), whereas in Model 3, we estimate a quadratic form equation since the coefficients for the cubic form in Model 2 end up being insignificant. Model 2 and 3 include the economic variables mentioned above in addition to income per capita.

The findings in the first column of Table 2 reveal that per capita industrial CO_2 emissions initially decline with rising per capita income, then start to rise after a certain income level is reached and finally decline again after a higher per capita income level. This finding does not support the EKC hypothesis, which would imply an inverted-U curve and hence $\beta_3 = 0$ in a cubic model specification. Instead, we are faced with a tilted-S curve with -, +, - signs for $\beta_1, \beta_2,$ and β_3 coefficients respectively. But one implication of the Model 1 results is that there is a point in time when industrial emissions start to decline when the Mediterranean countries reach a certain income point.

Besides, although not all the time dummies are significant in Model 1, some years, such as 2008, 2009 and 2010, contribute significantly to the decline of industrial emissions (as compared to the year 1971).[4]

Model 2 incorporates the impact of different factors together with per capita income (and its exponents) that might affect industrial CO_2 emissions in the Mediterranean region (see the second column in Table 2). This specification indicates the positive effects of industry, urbanization, population density and energy use on industrial CO_2 emissions. In other words, higher shares of industry value-added in total output, urban population, population density

[4]Regression outputs are displayed in Appendix C.

and energy use lead to increasing amounts of per capita emissions in the selected countries. Urbanization has the largest positive coefficient stimulating CO_2 emissions significantly. However, the tilted-S-shaped relationship between per capita income and emissions disappears once these economic variables are accounted for. Time accounts for part of the decrease in per capita emissions whereas income per capita becomes insignificant. Trade as a share of GDP also does not appear to be an influential factor for industrial emissions.

Table 2. Panel Fixed-effects Model Results (with robust (HAC) standard errors)

	Model 1 *Cubic form*	*Model 2* *Cubic form*	*Model 3* *Quadratic form*
	Coefficient *(Std. Error)*	*Coefficient* *(Std. Error)*	*Coefficient* *(Std. Error)*
const	84.00 **	-1.97	-19.03 ***
	(38.02)	(38.65)	(6.00)
lngdppc	-30.77 **	-1.98	3.90 ***
	(13.60)	(13.82)	(1.32)
sq_lngdppc	3.71 **	0.46	-0.22 ***
	(1.61)	(1.64)	(0.08)
tr_lngdppc	-0.15 **	-0.03	
	(0.06)	(0.06)	
industry		0.009 *	0.009 *
		(0.005)	(0.005)
urban		0.03 ***	0.03 ***
		(0.007)	(0.007)
popdens		0.002 ***	0.002 ***
		(0.0007)	(0.0007)
trade		-0.001	-0.001
		(0.001)	(0.001)
energyuse		0.0006 ***	0.0006 ***
		(0.0001)	(0.0001)
Time dummies	Yes	Yes	Yes
No. of observations	560	497	497
Adjusted R-squared	0.87	0.93	0.93

Since the cubic form equation turns out to have insignificant coefficients for *lngdppc*, *sq_lngdppc* and *tr_lngdppc*, once other variables are controlled for in Model 2, we attempt to run a quadratic regression to see whether there is an EKC relationship in case the controls are added together with time dummies. Model 3 reports the results from the quadratic form equation, where an inverted-U relationship is detected between per capita income and industrial emissions (see the third column in Table 2). This supports the EKC hypothesis for the countries selected and the turning point per capita GDP ($exp\ (-\beta_1/2\beta_2)$) corresponds to around 7,570 international dollars (at 2005 constant prices). This finding implies that some countries like Albania, Algeria, Egypt, Morocco, Syria and Tunisia have not reached the turning point income where their industrial emissions will start to decline, whereas some like Cyprus, France, Greece, Italy and Spain have already been enjoying the downward sloping portion of the EKC. On the other hand, some countries, including Turkey, reached the turning point around the mid-1990s.

What is more, the positive effects of industry, urbanization, population density and energy use are proven to be robust in the last specification as well. Trade intensity, on the other hand, appears to be insignificant. In sum, one could easily note that the selected Mediterranean countries have experienced an EKC relationship for industrial CO_2 emissions or will enjoy a reduction in their industrial pollution as their per capita income rises at some point in time depending on their characteristics related to industrial shares of total output, urban population, population density and the amount of energy use.

Most of these findings are in line with the previous studies that study industrial or total CO_2 emissions. Income per capita has usually been evidenced as a major factor that manipulates industrial emissions. Most of the EKC literature supports this finding for income. Needless to say, the shape of the relationship depends on the country, country group or time period investigated.

Environmental pollution tends to increase when economies switch from agriculture to industry; hence increases in industrial share of GDP are expected to worsen environmental degradation. The effect is also valid during the transition from industry to services and knowledge-based sectors. As manufacturing and construction value-added shares decline, industrial CO_2 emissions are found to decline in many studies (Panayotou, 1993; Komen et al., 1997; Vukina et al., 1999; Hettige et al., 2000).

In the pace of economic development, the move from rural to urban areas is almost inevitable. This trend is expected to increase environmental pollution since economic activity mostly takes place in urbanized areas and higher urban consumption leads to a higher demand for energy and resources. For instance, economic development has been associated with higher levels of urbanization and higher industrial emissions in China in a study that examines the period 1995-2009 (Zhou et al., 2012). Our results also confirm this phenomenon with a positive impact on industrial per capita CO_2 emissions.

Population pressure is found to be another contributing factor to increased CO_2 emissions. Several other studies also claim the same effect for population density (Grossman and Krueger, 1991; Panayotou, 1997). This translates into an environmental threat of increasing world population on emissions, although all other factors remain constant and the EKC relationship holds with a turning point of income.

In our analysis, the share of total trade in GDP, namely trade density, does not display a significant sign. What would be more convenient to mark here could be trade composition of economies instead of simply looking at the sum of exports and imports. For instance, the "pollution haven" hypothesis suggests that industries that pollute more would relocate their activities in countries where environmental regulations are less strict or do not exist at all. Hence, if a country starts importing the most polluting goods from other countries or regions, one would expect that industrial emissions would become lower, although the trade volume changes. Our study falls short of explaining these details for now.

Regarding the impact of energy use on industrial CO_2 emissions, IEA (2007: 20) reports that industrial energy use has been boosted importantly in recent decades with a different rate of growth in each sector. Sectors like chemicals, petrochemicals, cement, iron and steel have been consuming large amounts of energy, mostly fossil fuels, in expanding economies and this energy use has brought together higher dependence on fossil fuels. Country studies have also proven the fact that energy use is responsible for emissions increases. For instance, Lim et al. (2009) find that the energy sector is a major contributor to industrial emissions in Korea for the period 1990-2003 since the recent economic growth has largely gone along with increasing energy consumption in the economy. Krey et al. (2012) find evidence of the same impact on industrial CO_2 emissions for Chinese energy consumption growth together with total output increase. On the other hand, these findings imply that a structural shift from energy-intensive sectors towards services sectors would bring together a reduction in emissions.

These results offer hints to cope with the environmental effects of economic growth using appropriate policy tools related to population distribution, urbanization, industrialization and energy use.

5. Conclusion

Industry is a highly energy-intensive sector, intensively using fossil fuels, where carbon emissions from industry are dominated by the production of goods in certain sectors such as iron and steel, cement and chemicals and petrochemicals. Increasing activity in these sectors leads to further exploitation of fossil fuels and a rise in CO_2 emissions. Neither the level of energy use of the industry sector nor the type of energy used by the sector is expected to change significantly in the near future.

The environment of the Mediterranean region appears to be one of richest; but also, due to the intensity of trade and industry, one of the most vulnerable in the world. This fact makes national and supranational policies designed against environmental degradation a priority for the countries of the region. In this context, this paper examined the effects of GDP per capita, value added of industry, urban population, population density, trade intensity and energy use on CO_2 emissions from manufacturing industries and construction containing emissions from combustion of fuels in industry by employing panel fixed-effects estimations.

The analyses show that there is a tilted-S shaped relationship between GDP per capita and per capita industrial CO_2 emissions. But the S-curve relationship disappears once other explanatory factors such as industrial value added, urbanization, energy use and population dynamics are accounted for. However, a quadratic regression shows the existence of an EKC relationship even in the presence of control variables. Also the analysis using a quadratic regression detects the positive relation of per capita industrial CO_2 emissions with value added of industry, urban population, population density and energy use. Thus, the quadratic regression confirms that pollution tends to decrease in the selected Mediterranean countries after they reach a certain level of per capita GDP. However, this decreasing trend faces a risk of reversal in the absence of appropriate urban, industrial and energy policies. The analysis sets forth that the development of the tertiary sector in the region and the decrease in the relative contribution of the industrial sectors to the economy is expected to alleviate pollution. In addition, policies aimed at reducing rural-to-urban migration, and thus population density in urban areas, and the building of an energy policy based on the use of less fossil fuels appear as the policy priorities in order to enjoy the negatively-sloped part of the EKC in the Mediterranean region.

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Appendices

A. Summary statistics using the observations in the sample

Variable	Mean	Median	Minimum	Maximum
indCO2pc	0.689227	0.492344	0.000000	2.80160
gdppc	10814.8	6780.53	1079.70	32403.3
industry	33.0015	30.8617	16.0278	66.9380
urban	61.0051	60.4338	31.9344	94.6710
popdens	171.357	80.0113	5.94771	1299.98
trade	64.8482	54.7172	9.10230	188.977
energyuse	1407.02	988.079	154.731	4301.04

Variable	Std. Dev.	C.V.	Skewness	Ex. kurtosis
indCO2pc	0.539241	0.782385	0.904014	0.397004
gdppc	8628.54	0.797848	0.814675	-0.617357
industry	10.7487	0.325705	1.15687	0.930585
urban	15.6592	0.256687	0.243198	-0.801214
popdens	272.917	1.59268	3.01520	8.00398
trade	34.1635	0.526823	1.67786	2.62595
energyuse	1007.81	0.716273	1.03341	0.227589

B. Correlation matrix

Correlation coefficients, using the observations 1:01 - 14:40
(missing values were skipped)
5% critical value (two-tailed) = 0.0829 for n = 560

indCO2pc	gdppc	industry	urban	popdens	
1.0000	0.6540	-0.2915	0.1800	-0.3004	indCO2pc
	1.0000	-0.2385	0.6099	0.1816	gdppc
		1.0000	0.1540	0.4093	industry
			1.0000	0.6469	urban
				1.0000	popdens

trade	energyuse	
-0.3747	0.7245	indCO2pc
0.0025	0.9484	gdppc
0.3526	-0.2338	industry
0.5039	0.5854	urban
0.7753	0.1264	popdens
1.0000	-0.0333	trade
	1.0000	energyuse

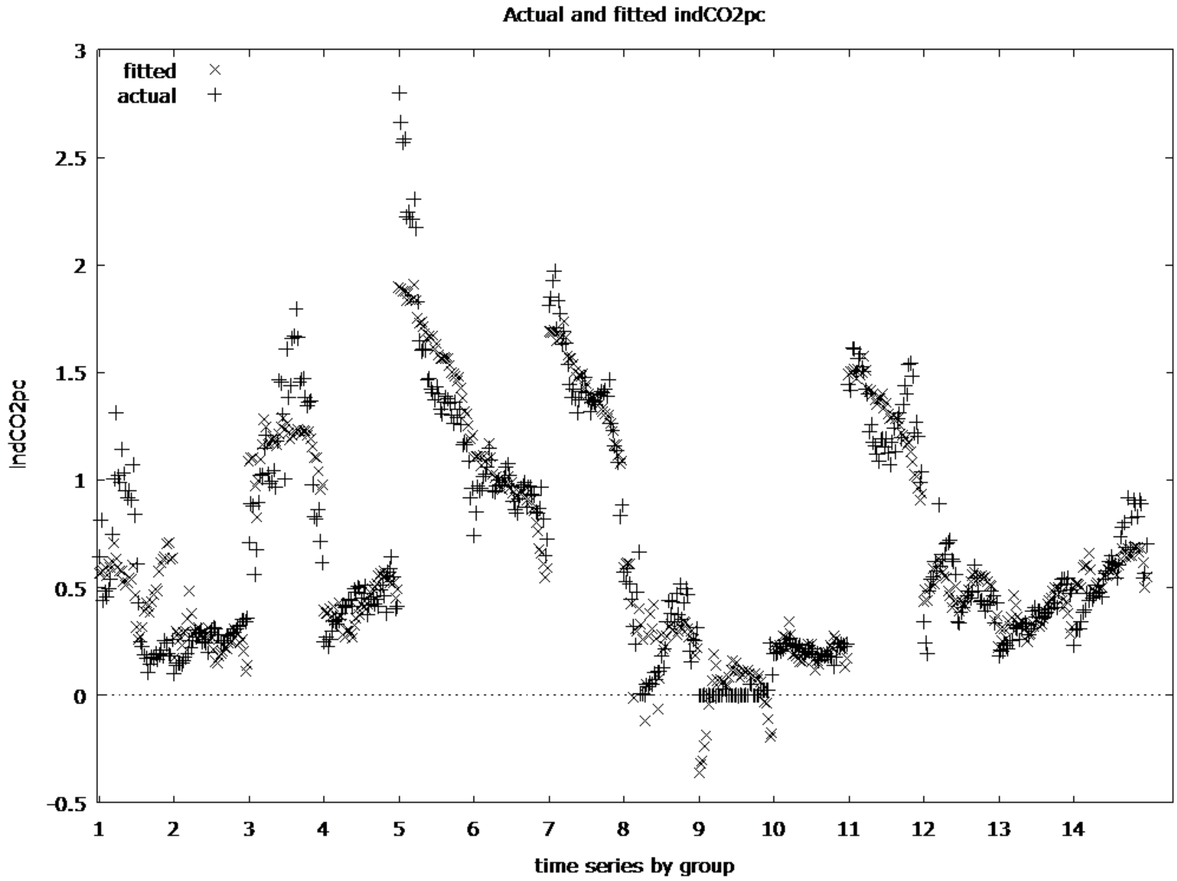
C. Regression Outputs and Fitted Plots

Model 1: Fixed-effects, using 560 observations
Included 14 cross-sectional units, time-series length = 40
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	84.0032	38.02	2.2094	0.02759	**
lngdppc	-30.7727	13.6029	-2.2622	0.02411	**
sq_lngdppc	3.7082	1.60838	2.3055	0.02154	**
tr_lngdppc	-0.145948	0.0628383	-2.3226	0.02060	**
dt_2	-0.00544326	0.0229316	-0.2374	0.81247	
dt_3	-0.00994076	0.035364	-0.2811	0.77875	
dt_4	-0.00357978	0.0325945	-0.1098	0.91259	
dt_5	-0.0492273	0.0507697	-0.9696	0.33270	
dt_6	-0.00683056	0.0613945	-0.1113	0.91146	
dt_7	-0.03237	0.057558	-0.5624	0.57410	
dt_8	-0.0208813	0.0613249	-0.3405	0.73362	
dt_9	0.0556157	0.0688846	0.8074	0.41983	
dt_10	-0.00939058	0.0681988	-0.1377	0.89054	
dt_11	-0.0924861	0.0775096	-1.1932	0.23334	
dt_12	-0.107845	0.0899597	-1.1988	0.23116	
dt_13	-0.102276	0.0952806	-1.0734	0.28360	
dt_14	-0.118631	0.0946348	-1.2536	0.21058	
dt_15	-0.146126	0.0941307	-1.5524	0.12120	
dt_16	-0.164823	0.0996172	-1.6546	0.09864	*
dt_17	-0.135326	0.102255	-1.3234	0.18630	
dt_18	-0.124931	0.100013	-1.2492	0.21219	
dt_19	-0.0961955	0.100024	-0.9617	0.33665	
dt_20	-0.149683	0.0988412	-1.5144	0.13056	
dt_21	-0.121822	0.0968989	-1.2572	0.20926	
dt_22	-0.170106	0.0961709	-1.7688	0.07753	*
dt_23	-0.198548	0.107937	-1.8395	0.06643	*
dt_24	-0.185094	0.111505	-1.6600	0.09754	*
dt_25	-0.167691	0.113613	-1.4760	0.14057	
dt_26	-0.172286	0.120605	-1.4285	0.15376	
dt_27	-0.159969	0.119076	-1.3434	0.17974	
dt_28	-0.168551	0.112632	-1.4965	0.13516	
dt_29	-0.181072	0.11707	-1.5467	0.12256	
dt_30	-0.162542	0.122464	-1.3273	0.18502	
dt_31	-0.1611	0.117139	-1.3753	0.16965	
dt_32	-0.183771	0.120848	-1.5207	0.12897	
dt_33	-0.162559	0.126425	-1.2858	0.19910	
dt_34	-0.196126	0.132624	-1.4788	0.13982	
dt_35	-0.229117	0.140855	-1.6266	0.10444	
dt_36	-0.273983	0.142209	-1.9266	0.05459	*
dt_37	-0.268336	0.148194	-1.8107	0.07078	*
dt_38	-0.330125	0.149419	-2.2094	0.02760	**
dt_39	-0.424241	0.161535	-2.6263	0.00889	***
dt_40	-0.40183	0.159543	-2.5186	0.01209	**

Meandependent var	0.689227	S.D. dependent var	0.539241
Sumsquaredresid	18.79436	S.E. of regression	0.193107
R-squared	0.884375	Adjusted R-squared	0.871758
F(55, 504)	70.08972	P-value(F)	2.5e-201
Log-likelihood	155.8208	Akaikecriterion	-199.6416
Schwarzcriterion	42.72286	Hannan-Quinn	-105.0045
rho	0.837947	Durbin-Watson	0.274000

Test fordifferinggroupintercepts -
Nullhypothesis: Thegroupshave a commonintercept
Test statistic: F(13, 504) = 123.164
with p-value = P(F(13, 504) > 123.164) = 4.72466e-147



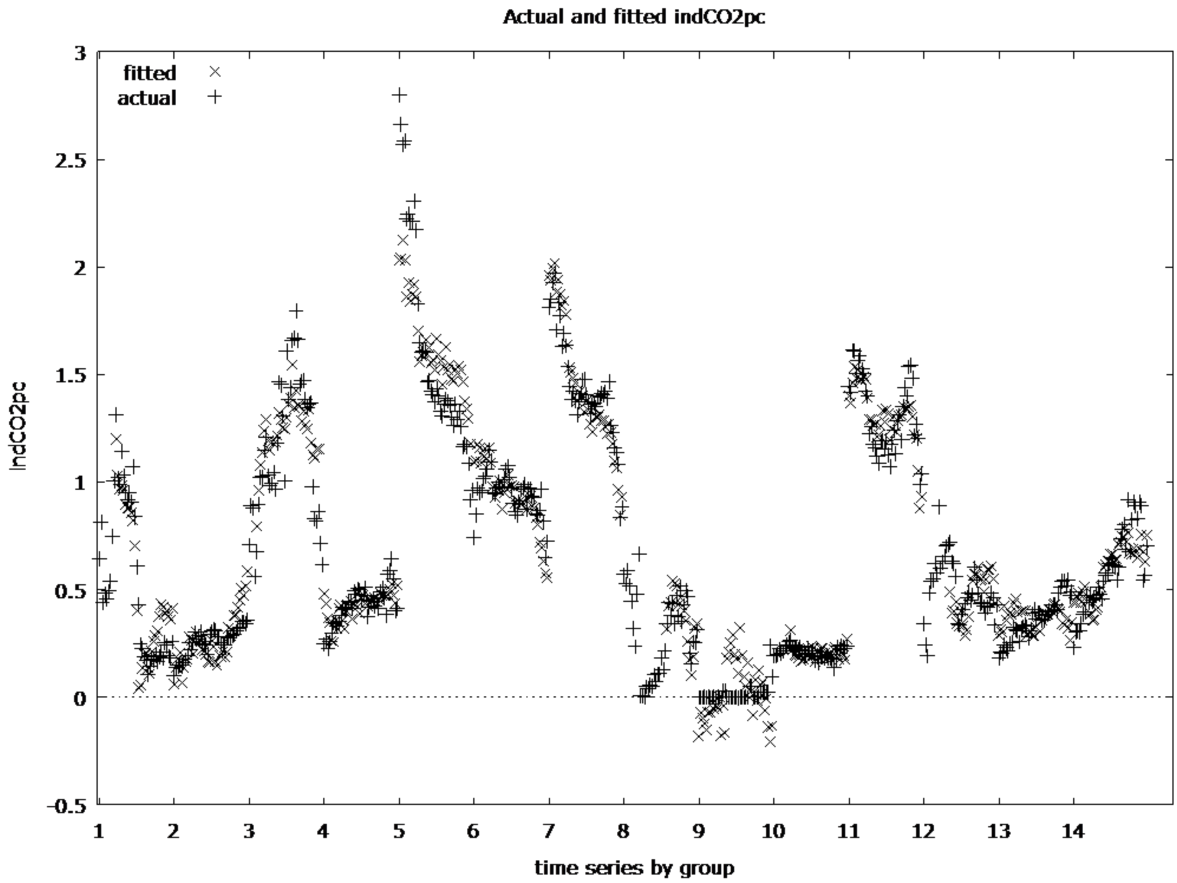
Model 2: Fixed-effects, using 497 observations
Included 14 cross-sectional units, time-series length: minimum 17, maximum 40
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	-1.97035	38.6503	-0.0510	0.95937	
lngdppc	-1.9765	13.8188	-0.1430	0.88633	
sq_lngdppc	0.459354	1.64379	0.2794	0.78003	
tr_lngdppc	-0.0258854	0.0647798	-0.3996	0.68965	
industry	0.00912292	0.00538928	1.6928	0.09121	*
urban	0.0260708	0.00690339	3.7765	0.00018	***
popdens	0.00188558	0.000690107	2.7323	0.00655	***
trade	-0.00115261	0.00106084	-1.0865	0.27786	
energyuse	0.000585649	0.000144734	4.0464	0.00006	***
dt_2	-0.070975	0.0314233	-2.2587	0.02440	**
dt_3	-0.0885041	0.0510695	-1.7330	0.08380	*
dt_4	-0.0843342	0.0487784	-1.7289	0.08453	*
dt_5	-0.169409	0.0720978	-2.3497	0.01923	**
dt_6	-0.190687	0.0851836	-2.2385	0.02569	**
dt_7	-0.217955	0.079122	-2.7547	0.00612	***
dt_8	-0.285259	0.0959016	-2.9745	0.00310	***
dt_9	-0.291172	0.0980068	-2.9709	0.00313	***
dt_10	-0.331614	0.117414	-2.8243	0.00496	***
dt_11	-0.426187	0.13164	-3.2375	0.00130	***
dt_12	-0.494803	0.141189	-3.5045	0.00050	***
dt_13	-0.50398	0.148402	-3.3960	0.00075	***
dt_14	-0.541602	0.154507	-3.5054	0.00050	***
dt_15	-0.561578	0.160401	-3.5011	0.00051	***
dt_16	-0.642767	0.170366	-3.7729	0.00018	***
dt_17	-0.637739	0.170454	-3.7414	0.00021	***
dt_18	-0.662155	0.174068	-3.8040	0.00016	***
dt_19	-0.69732	0.188929	-3.6909	0.00025	***
dt_20	-0.762137	0.20051	-3.8010	0.00016	***
dt_21	-0.73695	0.18498	-3.9839	0.00008	***
dt_22	-0.758073	0.197745	-3.8336	0.00014	***
dt_23	-0.819725	0.202082	-4.0564	0.00006	***
dt_24	-0.820292	0.193362	-4.2423	0.00003	***
dt_25	-0.812952	0.189035	-4.3005	0.00002	***
dt_26	-0.842408	0.202759	-4.1547	0.00004	***
dt_27	-0.856491	0.203512	-4.2086	0.00003	***
dt_28	-0.880098	0.213142	-4.1292	0.00004	***
dt_29	-0.921138	0.215499	-4.2744	0.00002	***
dt_30	-0.919265	0.216717	-4.2418	0.00003	***
dt_31	-0.939258	0.221433	-4.2417	0.00003	***
dt_32	-0.970352	0.228084	-4.2544	0.00003	***
dt_33	-0.985341	0.236668	-4.1634	0.00004	***
dt_34	-1.02677	0.236624	-4.3393	0.00002	***
dt_35	-1.0828	0.254631	-4.2524	0.00003	***
dt_36	-1.12194	0.263493	-4.2580	0.00003	***
dt_37	-1.11867	0.267801	-4.1773	0.00004	***

dt_38	-1.18741	0.267302	-4.4422	0.00001	***
dt_39	-1.23492	0.260467	-4.7412	<0.00001	***
dt_40	-1.18199	0.254763	-4.6395	<0.00001	***

Meandependent var	0.723134	S.D. dependent var	0.555243
Sumsquaredresid	9.548794	S.E. of regression	0.147990
R-squared	0.937555	Adjusted R-squared	0.928961
F(60, 436)	109.1016	P-value(F)	2.0e-226
Log-likelihood	276.9031	Akaikecriterion	-431.8062
Schwarzcriterion	-175.0822	Hannan-Quinn	-331.0422
rho	0.788221	Durbin-Watson	0.344530

Test fordifferinggroupintercepts -
Nullhypothesis: Thegroupshave a commonintercept
Test statistic: F(13, 436) = 64.1591
with p-value = P(F(13, 436) >64.1591) = 1.63163e-092



Model 3: Fixed-effects, using 497 observations
Included 14 cross-sectional units, time-series length: minimum 17, maximum 40
Robust (HAC) standard errors

	Coefficient	*Std. Error*	*t-ratio*	*p-value*	
const	-19.0304	5.99961	-3.1719	0.00162	***
lngdppc	3.90466	1.32165	2.9544	0.00330	***
sq_lngdppc	-0.21858	0.0771107	-2.8346	0.00480	***
industry	0.00917128	0.00528373	1.7358	0.08331	*
urban	0.0287269	0.00698984	4.1098	0.00005	***
popdens	0.00204544	0.000745903	2.7422	0.00635	***
trade	-0.00106507	0.00118628	-0.8978	0.36978	
energyuse	0.00058323	0.000142543	4.0916	0.00005	***
dt_2	-0.0724722	0.0329297	-2.2008	0.02827	**
dt_3	-0.0915193	0.0561576	-1.6297	0.10389	
dt_4	-0.0893838	0.0584237	-1.5299	0.12676	
dt_5	-0.17426	0.0806884	-2.1597	0.03134	**
dt_6	-0.195911	0.0949289	-2.0638	0.03963	**
dt_7	-0.226607	0.0934557	-2.4247	0.01572	**
dt_8	-0.295062	0.109368	-2.6979	0.00725	***
dt_9	-0.303848	0.11493	-2.6438	0.00849	***
dt_10	-0.347691	0.138442	-2.5115	0.01238	**
dt_11	-0.443483	0.155467	-2.8526	0.00454	***
dt_12	-0.51443	0.165484	-3.1086	0.00200	***
dt_13	-0.525679	0.178528	-2.9445	0.00341	***
dt_14	-0.565382	0.185017	-3.0558	0.00238	***
dt_15	-0.58823	0.19604	-3.0006	0.00285	***
dt_16	-0.670486	0.199464	-3.3614	0.00084	***
dt_17	-0.667182	0.202828	-3.2894	0.00109	***
dt_18	-0.694756	0.208141	-3.3379	0.00092	***
dt_19	-0.732132	0.224071	-3.2674	0.00117	***
dt_20	-0.798855	0.237729	-3.3604	0.00085	***
dt_21	-0.77501	0.225949	-3.4300	0.00066	***
dt_22	-0.797608	0.243145	-3.2804	0.00112	***
dt_23	-0.85955	0.24466	-3.5132	0.00049	***
dt_24	-0.863082	0.240908	-3.5826	0.00038	***
dt_25	-0.857357	0.240769	-3.5609	0.00041	***
dt_26	-0.887916	0.254829	-3.4844	0.00054	***
dt_27	-0.903612	0.254185	-3.5549	0.00042	***
dt_28	-0.928847	0.269543	-3.4460	0.00062	***
dt_29	-0.972181	0.272378	-3.5692	0.00040	***
dt_30	-0.973465	0.277673	-3.5058	0.00050	***
dt_31	-0.995575	0.281994	-3.5305	0.00046	***
dt_32	-1.02815	0.290897	-3.5344	0.00045	***
dt_33	-1.0444	0.297288	-3.5131	0.00049	***
dt_34	-1.08766	0.301656	-3.6056	0.00035	***
dt_35	-1.1454	0.320696	-3.5716	0.00039	***
dt_36	-1.18698	0.329255	-3.6051	0.00035	***
dt_37	-1.18595	0.334959	-3.5406	0.00044	***
dt_38	-1.25551	0.340746	-3.6846	0.00026	***

dt_39	-1.30113	0.338185	-3.8474	0.00014	***
dt_40	-1.24771	0.326828	-3.8176	0.00015	***

Meandependent var	0.723134	S.D. dependent var	0.555243
Sumsquaredresid	9.580374	S.E. of regression	0.148064
R-squared	0.937348	Adjusted R-squared	0.928889
F(59, 437)	110.8142	P-value(F)	3.9e-227
Log-likelihood	276.0826	Akaikecriterion	-432.1652
Schwarzcriterion	-179.6498	Hannan-Quinn	-333.0531
rho	0.789002	Durbin-Watson	0.343961

Test fordifferinggroupintercepts -
Nullhypothesis: Thegroupshave a commonintercept
Test statistic: F(13, 437) = 77.1726
with p-value = P(F(13, 437) >77.1726) = 2.57619e-104