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Does Financial Development Affect Environmental Degradation? Evidence from the OECD Countries

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ABSTRACT
In this study, building a simple model that incorporates static and dynamic elements, the relationship of financial development and economic growth to environmental degradation is investigated together with the validation of the Environmental Kuznets Curve (EKC) hypothesis. Our analysis is based on an unbalanced panel data set covering the OECD countries over the period 1970–2014. Our approach thoroughly accounts for the presence of cross-sectional dependence between the sample variables and utilizes second generation panel unit root tests in order to investigate possible cointegration relationships. The empirical findings do indicate that local (NO_x per capita emissions) and global (CO_2 per capita emissions) pollutants redefine the EKC hypothesis when we account for the presence of financial development indicators. Specifically, in the case of global pollution an N-shape relationship is evident in both static and dynamic frameworks, with a very slow adjustment. Lastly, our study calls for a strengthening of the effectiveness of environmental degradation policies by ensuring sustainability of the OECD banking system in order to drastically reduce emissions.

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Introduction

DURING THE LAST YEARS THERE HAS BEEN A VAST BODY OF LITERATURE EXAMINING THE VALIDITY OF THE ENVIRONMENTAL KUZNETS curve (EKC) hypothesis using panel data techniques (parametric and semiparametric models) with controversial results (Apergis *et al.*, 2014; Halkos, 2013, 2003; Halkos and Tsionas, 2001; Cole, 2004; Millimet *et al.*, 2003; Zaim and Taskin, 2000; Holtz-Eakin and Selden, 1995).[1]

At the same time the effects of financial development and economic growth on pollutants' emissions can be decomposed into three different elements: scale, technique and composition effects. More specifically, the greater the financial and economic activity the greater will be the emissions as more inputs are used (*scale* effect). However, an increase in the level of economic activity may raise serious environmental concerns, thus leading to a reduction in the level of anthropogenic emissions (i.e. greenhouse gas emissions) triggered by the use of cleaner technologies in the production process. The latter justifies the existence of the *technique* effect (Grossman and Krueger, 1995). In

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[1]The EKC hypothesis implies a non-linear relationship of an inverted U type between environmental degradation and economic growth.

other words, as income rises it is likely that the demand for cleaner goods also increases. This may induce firms to alter production methods and reduce pollution (*composition* effect). As a consequence, the EKC hypothesis justifies the scale effect dominating the composition effect at lower income levels, but as income reaches a critical threshold (turning point) the latter effect offsets the former (Halkos, 2013; Jayanthakumaran and Liu, 2012).

Despite the plethora of studies devoted to this topic, existing studies suffer from two shortcomings. First, they assume that the variables or the random disturbances are not correlated across the panel dimension, justifying the existence of cross-sectional independence. However, it is common for macro-level data to violate this assumption, which will result in low power and size distortions of tests that assume cross-sectional independence. The latter may arise due to common unobserved effects triggered by changes in environmental legislation in the OECD countries. Therefore, cross-sectional independence is a strong assumption that has to be tested rather than assumed in order to avoid misleading results.

Second, none of the existing studies account for the interdependence between the financial development proxied by structural indicators (i.e. credit, stock and bonds) and economic growth under the presence of local and global pollutants such as NO_x and CO_2 emissions respectively, which in our models acts as a driving force to reveal the validity of the EKC hypothesis. One of the most profound reasons for justifying the inclusion of financial development indicators in the standard EKC literature is linked with the fact that an improved financial and banking system may attract Foreign Direct Investments (FDIs) to the OECD host countries, which in turn may act as a catalyst to economic growth (Frankel and Romer, 1999). Moreover, financial development triggers the use of clean and environmentally friendly technologies, thus achieving a higher level of economic development and less pollution (Birdsall and Wheeler, 1993; Frankel and Rose, 2002; Tamazian and Rao, 2010; Dögl and Behnam, 2015). Last, as pointed out by Tamazian and Rao (2010), financial development may also result in more industrial pollution and environmental degradation.

As mentioned, our intention is to explore the effect of financial development and economic growth on environmental degradation. The stock and bond markets differ in the risk involved in investing in both. Investing in bond markets may be less risky in comparison with stock markets, as the former are less volatile. At the same time, bond prices fluctuate with changes in market sentiments and in different economic circumstances in a significantly different way and according to different factors compared with stocks. Different factors such as interest rates and economic motivation policies have an influence on both stocks and bonds with opposite reactions. If stocks are in an increasing trend, investors may move away from bonds and towards the booming stock market, while if stock markets stabilize or severe economic problems arise investors return to the safety of bonds.

This study aims to contribute to the financial development–economic growth nexus by building a simple model within a static and dynamic framework to investigate the validity of the environmental Kuznets curve (EKC) hypothesis. One of the main novelties of the paper is that it thoroughly accounts for the presence of cross-sectional dependence (CD) through the suggested Pesaran (2004) CD tests. Moreover, in contrast to the existing literature (see for example Omri *et al.*, 2015) it utilizes the appropriate 'second generation' panel unit root tests in order to uncover possible cointegrated relationships, an issue that has been overlooked by the existing empirical literature on EKC. The reason for using this kind of unit root testing can be justified by the fact that traditional stationarity tests (known as 'first generation' tests) suffer from size distortions and ignorance of CD (Apergis, 2016). The empirical findings do indicate that local (NO_x per capita emissions) and global pollutants (CO_2 per capita emissions) redefine the validity of the EKC hypothesis when we account for the presence of financial development indicators.

The rest of this paper is as follows. The following section reviews the empirical literature. The next section describes the data and the econometric methodology used in the empirical analysis. The fourth section reports the main empirical findings along with the necessary tests for CD. Lastly, the fifth section concludes the paper and provides some policy implications.

Review of the Literature

The literature on the EKC hypothesis starts with the pioneering study by Grossman and Krueger (1995), who examined the reduced-form relationship between per capita income and various environmental indicators (i.e. air pollution, river oxygen regime, contamination of river basins) to conclude that environmental quality gradually deteriorates with economic growth (inverted U shape).

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The majority of the empirical studies regarding EKC use econometric models (i.e. non-linear log models, error correction models, VAR/VECM etc) dealing with stationarity and cointegration properties, where the dependent variable is usually the (per capita) level of pollutants (i.e. CO_2 emissions, NO_x and SO_2 emissions, etc) regressed on different polynomials (powers) of (per capita) GDP, and other covariates including *inter alia* various efficiency indicators (see for example Halkos, 2003, 2013; López-Menéndez *et al*., 2014; Halkos and Tzeremes, 2009, 2013; Managi and Kaneko, 2006; Shen, 2006, 2008; Stern, 2004). The vast majority of these studies agree that there is an inverted U shape between the level of environmental pollution and economic growth, implying the validity of the EKC hypothesis. However, a recent study by Halkos and Polemis (2016) argues that global pollutants such as CO_2 emissions exhibit an N shape, implying that environmental damage starts rising again after a fall to a specific turning point.

On the other hand, relatively few empirical studies adopt a simultaneous equation system to address the impact of economic growth on environmental degradation. Dean (2002) uses a panel simultaneous equation system drawn from a Heckscher–Ohlin model in order to capture certain effects of trade liberalization on the environmental quality (water pollution). His findings suggest that there is a direct negative trade effect on environmental damage, which is fully reversed when the income growth is taken into account. In the paper by Jayanthakumaran and Liu (2012) an array of econometric techniques is applied, ranging from a quadratic log function specification to a SUR system similar to Dean's approach, to provide little support in favor of the EKC hypothesis.

The existing empirical literature on environmental pollution and financial developments is still in its infancy, with controversial results since the researchers acknowledge that emissions may have positive as well as negative effects on financial development (Halkos and Sepetis, 2007; He and Wang, 2012; Omri *et al*., 2015). In the seminal paper of Frankel and Romer (1999) it is argued that, during the process of financial development, developing countries will be motivated toward the adoption of cleaner energy technologies, which is a move to reduce the environmental effects. Moreover, they claim that financial development is the driving force for the companies to obtain capital and reduce financing costs by adopting environmentally friendly techniques. This finding is also evident in the study of Yuxiang and Chen (2010), who argue that promoting financial development policies is a key issue in order to stimulate technological spillovers, which in turn reduce CO_2 emissions and enhance domestic production. Similarly, Cole and Elliot (2005) examine the impact between financial development and environmental degradation as expressed by CO_2 emissions. In their study, they claim that financial tools such as loans, leasing, factoring, treasury bonds and derivatives allow medium and large scale firms to achieve economies of scale, thereby reducing the use of resources as well as CO_2 emissions.

In another study, Tamazian *et al*. (2009) examine the impact of financial development on environmental quality in BRIC economies over the period 1992–2004. They claim that a higher degree of economic and financial development decreases the environmental degradation and vice versa. Therefore, policy makers and government officials should pursue policies targeting financial openness and trade liberalization in order to boost FDIs and thus limit the level of environmental pollution in the sample countries. Similarly, Tamazian and Rao (2010) portray financial development as playing a positive role in environmental disclosure of the transitional economies. In particular, they argue that higher levels of FDI help to achieve lower CO_2 emissions, while financial liberalization may be harmful if not accompanied by a strong institutional framework. Based on these findings, the study claims that policies must focus on establishing strong institutional structures that have long term benefits for combating greenhouse gas emissions (GGEs) and global warming. Moreover, the promotion of new and more efficient technologies that lead to a less carbon-intensive economy should be high on the policy agenda.

In a recent study, Nasreen *et al*. (2017) use cointegrated techniques to investigate the relationship between financial stability, economic growth, energy consumption and CO_2 emissions in South Asian countries over the period 1980–2012. They argue that financial stability improves environmental quality, supporting an inverted U-shaped curve. It is worth emphasizing that the study acknowledges a unidirectional causality running from financial stability to environmental pollution, which is limited to only two sample countries. Moreover, Abid (2017), tests the hypothesis of the EKC using generalized method of moments (GMM) panel data techniques in a mixed data set comprising Middle East-African and EU countries respectively over the period 1990–2011. This study uses *inter alia* institutional quality variables such as public expenditures, financial development (domestic credit to the private sector), trade openness and FDIs in order to examine the validity of the EKC hypothesis. The empirical findings suggest

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a monotonically increasing relationship between CO_2 emissions and GDP in all of the sample countries, thus rejecting the inverted U-shape curve.

On the other hand, there are some studies arguing that financial development creates a negative impact on the environment. More specifically, Zhang (2011) argues that financial development leads to inefficiency, increasing toxic release emissions. Shahbaz and Lean (2012) study the impact of financial development on environmental quality, claiming that an organized financial sector attracts FDIs, which then stimulate the efficiency of the operation of the stock market and economic activity, leading to an increasing path of CO_2 emissions. It is also interesting to mention that there are some studies that found a neutral interaction between financial development as expressed by some proxy variables (i.e. treasury bonds, non-performing loans, credit risk, stocks etc) and the level of environmental awareness (Ozturk and Acaravci, 2013).

In a recent study, Lee *et al.* (2015) investigate the validity of the EKC hypothesis between the level of global pollutants (CO_2 emissions) and financial development for a panel dataset consisting of 25 OECD countries over the period 1971–2007. The authors use panel fully modified OLS estimators (FMOLS), rejecting the existence of the EKC for their sample countries. Last, Shahbaz *et al.* (2016) re-examine the asymmetric impact of financial development on environmental quality in Pakistan for the period 1985–2014 using quarterly data. Their approach is similar to ours in the sense that they use comprehensive indices of financial development generated by using bank and stock market based financial development indicators. They claim that inefficient use of energy negatively affects the level of environmental quality, implying that the adoption of energy efficient technology is of paramount importance.

Based on the above, the existing studies do not properly incorporate the spillovers generated by the inclusion of financial development in the standard EKC hypothesis since they fail to control for the presence of CD, which is evident in nearly all of the panel data studies (Pesaran, 2004). Moreover, they do not address the impact of structural banking and other financial characteristics such as the level of private credit by deposit money banks, the listed shares in a stock market and the corporate bond issuance, all well documented in the finance literature (see among others Luintel *et al.*, 2008; Weber *et al.*, 2008; Antzoulatos *et al.*, 2011). The purpose of this study is to fill these research gaps by combining certain environmental determinants from a macro- and a micro-economic perspective. The reason for using variables from a macro- (i.e. GDP) and a micro-economic level (i.e. credit, stock and bond indicators) can be explained by the fact that financial development may generate pollution, since in a more developed economy, characterized by the strong presence of banking penetration, firms are more prone to undertake actions that hinder the level of environmental concern. On the other hand, a more profoundly developed financial system may help in financing the development of the tertiary sector, which leads to pollution reduction. Therefore, in order to test for the EKC hypothesis and the shape of the curve between emissions and economic growth in an efficient and proper manner, micro level variables on environmental degradation have to be included.

Data and Methodology

The econometric estimation was based on an unbalanced panel of 34 OECD countries covering the period 1970–2014 ($n = 34$ and $T = 44$).[2] The latter was dictated by data availability. The environmental variables entering the models (CO_2, and NO_x per capita emissions measured in metric tons of CO_2 equivalent) are obtained by the World Bank (World Development Indicators Database). The banking development indicators were drawn from the World Bank (Financial Development and Structure Database) and were selected following the existing literature (see for example Antzoulatos *et al.*, 2011). More specifically, we use the private credit by deposit money banks as a percentage of GDP (CREDIT). This indicator denotes the financial resources provided to the private sector by domestic money banks as a share of GDP. Domestic money banks comprise commercial banks and other financial institutions that accept transferable deposits, such as demand deposits. The other indicator (STOCK) is the stock market capitalization to GDP and includes the total value of all listed shares in a stock market as a percentage of GDP.

[2]These include the following countries: Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovakia, Spain, Sweden, Switzerland, Turkey, United Kingdom and United States.

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Variable	Obs.	Mean	Standard deviation	Min.	Max.
Dependent variables					
CO_2	1399	9.083	5.087	1.230	40.59
NO_x	1530	1.054	0.758	0.150	4.940
Explanatory variables					
GDP	1365	24 857	14 708	1968	87 773
CREDIT	1393	64.59	39.04	3.320	262.5
STOCK	1077	49.75	40.87	0.180	250.0
BOND	496	1.845	1.850	0.000	18.07
FININDEX	1259	−0.585	0.927	−4.605	1.803

Table 1. Summary statistics

The third financial development indicator (BOND) stands for the corporate bond issuance volume to GDP and denotes the ratio of newly issued corporate bonds by private entities in industries other than finance, holding companies and insurance, divided by GDP in current USD.

Table 1 depicts the main descriptive statistics from the model variables. We must stress that, due to the lack of sufficient comparable data, we could not include other banking development indicators such as central bank assets to GDP, credit to bank deposits and non-performing loans to gross loans. Lastly, the level of per capita real GDP (in 2005 USD prices) by OECD country is also drawn from the Financial Development and Structure Database.

Where appropriate, interpolation was used in the case of missing values, while moving average and single and double exponential smoothing techniques were applied to predict the missing values of the variables of interest for recent years of the time period considered. The choice of the appropriate method was determined with the help of measures of accuracy such as Mean Absolute Percentage Error (MAPE), Mean Absolute Deviation (MAD) and Mean Squared Deviation (MSD).[3]

The Proposed Econometric Methods

Similarly to other empirical studies (see for example Millimet *et al.*, 2003; Zarzoso and Morancho, 2004; Apergis, 2016), we first estimate separately the following (polynomial) panel data models in a static form[4]:

$$CO_{2it} = \alpha_i + \beta_t + b_0 + b_1 GDP_{it} + b_2 GDP_{it}{}^2 + b_3 GDP_{it}{}^3 + c_1 CREDIT_{it} + c_2 STOCK_{it} + c_3 BOND_{it} + e_{it} \tag{1}$$

$$NO_{xit} = \alpha_i + \beta_t + b_0 + b_1 GDP_{it} + b_2 GDP_{it}{}^2 + b_3 GDP_{it}{}^3 + c_1 CREDIT_{it} + c_2 STOCK_{it} + c_3 BOND_{it} + e_{it} \tag{2}$$

$$i = 1, 2, \ldots, 34 \text{ and } t = 1, 2, \ldots, 44$$

where CO_{2it} and NO_{xit} are the per capita global and local pollutants in country i at time t; α_i and β_t are state and time fixed effects used in order to capture common factors across the cross-sectional element; GDP_{it} is real GDP per capita (powers) for country i at time t, and CREDIT, STOCK and BOND have been defined above. Finally, e_{it} are zero mean i.i.d. errors.

[3]The use of these statistics helps us to compare different forecasting fits and smoothing procedures, with smaller values indicating a better fitting model.
[4]The degree of the polynomial for each equation has been determined by the maximum number of statistically significant powers. For example, in the case of NO_x fourth and higher degree polynomial specifications have the extra powers of GDP to be not statistically significant.

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The basic model of unobserved effects may be expressed as

$$y_{it} = X_{it}\beta + d_i + \varepsilon_{it} \qquad t = 1, 2, ..., T \tag{3}$$

where X_{it} is $1 \times K$. The first method used is the fixed effects (FE) estimator, allowing a different intercept for every country and treating the constants as regression parameters. Specifically, as will be shown next, in the random effects (RE) specification d_i is put into the error term assuming d_i is orthogonal to X_{it}, while in the FE it is allowed to be randomly correlated with X_{it}, with (3) expressed as

$$\hat{\beta}_{\mathrm{FE}} = \frac{\sum_{i=1}^{N}\left[\left(X_{it} - \overline{X}_i\right)'\left(Y_{it} - \overline{Y}_i\right)\right]}{\sum_{i=1}^{N}\left[\left(X_{it} - \overline{X}_i\right)'\left(X_{it} - \overline{X}_i\right)\right]} \tag{4}$$

and the feasible generalized least squares (FGLS) is given as

$$\hat{\beta}_{\mathrm{FEGLS}} = \frac{\sum_{i=1}^{N}\left[\left(X_{it} - \overline{X}_i\right)'\hat{\Omega}^{-1}\left(Y_{it} - \overline{Y}_i\right)\right]}{\sum_{i=1}^{N}\left[\left(X_{it} - \overline{X}_i\right)'\hat{\Omega}^{-1}\left(X_{it} - \overline{X}_i\right)\right]} \qquad \text{with } \hat{\Omega} = \frac{\sum\left[\left(\varepsilon_{it} - \bar{\varepsilon}_i\right)\left(\varepsilon_{it} - \bar{\varepsilon}_i\right)'\right]}{N} \tag{5}$$

In the FE specification the within transformation for consistent estimators requires T to be large. When we refer to the full set of countries it may be logical to assume that the model is constant. However, if the sampled cross-sections are derived from a large population and individual effects are strictly uncorrelated with the regressors, it may be suitable to model the individual intercepts as randomly distributed across cross-sections (Greene, 2003).[5]

In the RE analysis d_i is entered into the error term and (3) becomes

$$y_i = X_i\beta + u_i \tag{6}$$

with $u_i = d_i j_T + \varepsilon_i$, where j_T is a $T \times 1$ vector of ones. The unconditional variance of u_i may be expressed as a $T \times T$ matrix of the form $\Omega = \mathrm{E}\left(u_i u_i'\right)$, assuming it is positive definite. To apply an FGLS we form a $T \times T$ positive definite matrix of the form

$$\hat{\Omega} = \sigma_\varepsilon^2 \mathrm{I}_\mathrm{T} + \sigma_d^2 j_\mathrm{T} j_T' \tag{7}$$

with

$$\hat{\beta}_{\mathrm{RE}} = \frac{\left(\sum_{i=1}^{N} X_i'\hat{\Omega}^{-1}y_i\right)}{\left(\sum_{i=1}^{N} X_i'\hat{\Omega}^{-1}X_i\right)} \tag{8}$$

In the RE individual effects are treated as random, and constants are components of the random disturbances. Both FE and RE are inefficient in the presence of heteroskedasticity (Greene, 2003; Baltagi, 2002), and to tackle heteroskedasticity and various patterns of correlation between residuals generalized least squares (GLS) specifications

[5]In our case, although we examine the OECD countries as a specific group, we still consider that these sampled cross-sections are derived from a larger population. As a consequence, we rely on the RE model without considering the Hausman test when we account for the inconsistency of the RE estimates.

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may be used (Grossman and Krueger, 1995). We may also assume that the n disturbance terms at t, ε_t, follow a multinomial normal distribution with zero mean and $n \times n$ covariance matrix. The log likelihood function is given by

$$\ln(\beta, \Sigma|n) = \frac{nT}{2} \ln\ 2\pi - \frac{T}{2} \ln|\Sigma| = \frac{1}{2} \sum_{t=1}^{T} u_t' \Sigma^{-1} u_t \tag{9}$$

with

$$u_{it} = y_{it} - X_{it}' \beta \qquad i = 1,\ 2,\ \ldots,\ n \text{ and} \qquad \hat{\sigma}_{ij} = \frac{\hat{u}_t' \hat{u}_t}{T}.$$

The aforementioned analysis was performed in a static framework. With the intention to examine the robustness of our empirical findings allowing for dynamic aspects we use dynamic panel data techniques such as difference generalized method of moments (DIF-GMM) estimators attributed to Arellano and Bond (1991) and system generalized method of moments (SYS-GMM) estimators proposed by Arellano and Bover (1995) and Blundell and Bond (1998) respectively. The use of the latter is mainly justified as it significantly improves the estimates' accuracy and enlarges efficiency when the lagged dependent variables are considered as poor instruments as in the first differenced regressors (Greene, 2003; Baltagi, 2002; Li and Lyons, 2012; Harrington *et al.*, 2014; Abid, 2017). As a consequence, the SYS-GMM gives more robust results than the first differenced GLS and GMM estimation methods (Bond *et al.*, 2001; Hausman and Ros, 2013).

In our case and in modelling dynamic effects we have the lagged dependent variable among the RHS variables in the following form:

$$Y_{it} = X_{it}'\beta + \delta Y_{i,t-1} + \alpha_\iota + u_{it} \qquad I = 1, 2, \ldots, N, t = 1, 2, \ldots, T \tag{10}$$

where δ is a scalar, X_{it}' a $1 \times K$ and β a $K \times 1$, and u_{it} follow a one-way error component model ($u_{it} = \mu_i + v_{it}$), with μ_i: $\mathrm{IID}\left(0, \sigma_\mu^2\right)$ and v_{it}: $\mathrm{IID}\left(0, \sigma_v^2\right)$ independent both of each other and between them. Then the first difference GMM estimation is given as

$$\hat{\delta}_{GMM} = \frac{\left(\sum_{i=1}^{N} \Delta y_{i,t-1} Z_i\right) W_N \left(\sum_{i=1}^{N} Z_i' \Delta y_i\right)}{\left(\sum_{i=1}^{N} \Delta y_{i,t-1} Z_i\right) W_N \left(\sum_{i=1}^{N} Z_i' \Delta y_{i,t-1}\right)} \tag{11}$$

with the choice of W_N being important and the first step consistent estimator of d being

$$W_N^* = \frac{1}{\left(\frac{1}{N} \sum_{i=1}^{N} Z_i' \Delta \hat{\varepsilon}_i Z_\iota\right)} \tag{12}$$

In (3), if X_{it} are predetermined with current and lagged X_{it}s uncorrelated with the current term, then $E(X_{ij}u_{is}) = 0$ for $s \geq t$. A combination of strictly exogenous and predetermined X variables may be more realistic compared with the two extreme cases, with matrix Z_i adjusted according to each case.

Arellano and Bover (1995) integrated this approach with the instrumental variables of Hausman and Taylor (1981), with individual series being highly persistent and δ being near to unity. In such circumstances FD-GMM may present finite sample biases as the instruments are weak (Baltagi, 2002). Estimators using moment conditions relying on levels and FD refer to system GMM (Blundell and Bond, 2000).

Based on the above, the dynamic specifications of all the three models are given by the following reduced form equations:

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$$CO_{2it} = \alpha_i + \beta_t + b_0 + \sum_{l=1}^{L} d_{l,i} CO_{2it-l} + \sum_{m=0}^{M} b_1 GDP_{it-m} + b_2 GDP^2{}_{it} + b_3 GDP^3{}_{it} + c_1 CREDIT_{it} + c_2 STOCK_{it} + c_3 BOND_{it} + e_{it} \quad (13)$$

$$NO_{xit} = \alpha_i + \beta_t + b_0 + \sum_{l=1}^{L} d_{l,i} NO_{xit-l} + \sum_{m=0}^{M} b_1 GDP_{it-m} + b_2 GDP^2{}_{it} + b_3 GDP^3{}_{it} + c_1 CREDIT_{it} + c_2 STOCK_{it} + c_3 BOND_{it} + e_{it} \quad (14)$$

i = 1, 2, ..., 34, t = 1, 2, ..., 44 and l is the time lag operator for the dependent variable.

Results and Discussion

Cross-Section Dependence

One of the additional complications that arise when dealing with panel data compared with the pure time-series case is the possibility that the variables or the random disturbances are correlated across the panel dimension. The early literature on unit root and cointegration tests adopted the assumption of no CD. However, it is common for macro-level data to violate this assumption, which will result in low power and size distortions of tests that assume cross-sectional independence. For example, CD in our data may arise due to common unobserved effects as a consequence of changes in OECD environmental legislation. Therefore, before proceeding to unit root and cointegration tests we test for CD. We use the CD tests proposed by Pesaran (2004). The tests are based on the estimation of the linear panel model of the form

$$y_{it} = \alpha_i + \beta_i^{'} x_{it} + u_{it}, i = 1, ..., N; t = 1, ..., T \quad (15)$$

where T and N are the time and panel dimensions respectively, α_i the country-specific intercept, x_{it} a $k \times 1$ vector of regressors and u_{it} the random disturbance term. The null hypothesis in both tests assumes the existence of cross-sectional correlation: $\mathrm{Cov}(u_{it}, u_{jt}) = 0$ $Cov(u_{it}, u_{jt}) = 0$for all t and for all $i \neq j$. This is tested against the alternative hypothesis that $\mathrm{Cov}(u_{it}, u_{jt}) \neq 0$ for at least one pair of i and j. The Pesaran (2004) tests are a type of Lagrange-multiplier test that is based on the errors obtained from estimating Equation (20) by the OLS method.

Based on the above, we carry out the first part of the empirical analysis by examining the presence of CD. We use the CD tests proposed by Breusch and Pagan (1980) and Pesaran (2004). Both tests strongly reject the null hypothesis of cross-sectional independence (P-value = 0.000) for all the models, providing evidence of CD in the data given the statistical significance of the CD statistics (see Table 2). In face of this evidence we proceed to the existence of unit roots using tests that are robust to CD (the so-called 'second generation' tests).

Unit Root and Cointegration Testing

To examine the stationarity properties of the variables in our models we use the 'second generation' unit root tests for panel data. The unit root testing methodology allows for non-linear functions of the I(1) variables, which is really the case here as GDP enters both in levels and in quadratic and cubed form (Apergis, 2016). To this end, the empirical analysis makes use of the Fisher test as proposed by Maddala and Wu (1999) and developed by Kyung *et al.* (2003). This test explicitly considers cross-sectional dependency in an unbalanced panel data set. More specifically, this methodological approach is based on the p-values of individual unit root tests and assumes that all series are non-stationary under the null hypothesis, against the alternative that at least one series in the panel is stationary. Unlike the Im–Pesaran–Shin (1997) test, Fisher's test does not require a balanced panel. The results are reported in

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Variable	CD test	*P*-value	Correlation	Absolute (correlation)
CO_2	11.20***	0.000	0.076	0.546
NO_x	85.13***	0.000	0.536	0.682
GDP	132.95***	0.000	0.942	0.942
GDP^2	131.44***	0.000	0.930	0.930
GDP^3	129.62***	0.000	0.917	0.917
CREDIT	63.29***	0.000	0.428	0.571
STOCK	63.09***	0.000	0.497	0.543
BOND	30.22***	0.000	0.330	0.402
FININDEX	29.59***	0.000	0.241	0.413

Table 2. Cross-section dependence (Pesaran CD test)
Under the null hypothesis of cross-sectional independence the CD statistic is distributed as a two-tailed standard normal. Results are based on the test of Pesaran (2004). The *p*-values are for a one-sided test based on the normal distribution. Correlation and Absolute (correlation) are the average (absolute) value of the off-diagonal elements of the cross-sectional correlation matrix of residuals obtained from estimating Equations 1–2.
***Significant at 1%

Table 3, and they support the presence of a unit root across all sample variables. In other words, the test results suggest that no variables are integrated of an order greater than one (I-1).[6]

In order to investigate whether a long run equilibrium relationship exists among the variables in our three models, we implement two cointegration tests proposed by Westerlund (2007) that allow for CD and rely on the assumption of weakly exogenous regressors (Demetriades and James, 2011). In general, the tests constitute an error-correction approach to examining for cointegration that is based on the statistical significance of the error correction term. The intuition behind this approach is that if there is a long run relationship between the variables in our model we can estimate a regression that allows us to estimate the error-correcting terms which reflect the response of the system to random shocks that 'push' the system towards its long run equilibrium point. If the error-correction terms are significantly different from zero across sections, then there is evidence in favor of the existence of a long run relation. The null hypothesis in both tests is that of no cointegration.

The test statistics of the first two tests, denoted G_t, are general enough to allow for individual-specific intercepts and short run dynamics and are constructed as a weighted average of the estimated error-correcting coefficients across each province in our model. The alternative hypothesis in this test of tests is that at least one section in the panel is cointegrated. The second test assumes that the intercept is the same across sections and tests against the alternative hypothesis that the panel is cointegrated as a whole. The test statistic is denoted by p_t. The results of the tests are presented in Table 4; the critical values were created using a bootstrapping method. The results indicate that the first test rejects the null hypothesis of no cointegration for all three models. However, the second test that restricts the intercept to be the same across all provinces fails to reject the null.[7]

Empirical Findings

Using simple OLS to estimate the cointegrating relation will lead to bias in the estimated coefficients unless all of the explanatory variables are strongly exogenous. Furthermore, other OLS estimators that remove the endogeneity bias such as the fully modified OLS (Pedroni, 1999) or the dynamic OLS (Kao and Chiang, 2000) are inadequate for our data since they assume cross-sectional independence. As Pesaran and Smith (1995) point out, other traditional methods for estimating pooled models such as the fixed effects and the instrumental variables estimators proposed

[6]The test was carried out in STATA using the *xtfisher* routine.
[7]The tests can be carried out in STATA using the *xtwest* routine. It should be noted that the results are sensitive to the selection of the lag structure of the model. Persyn and Westerlund (2008) point out that this sensitivity might occur in small datasets.

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Variable	Statistic			
	P	Z	L^*	P_m
Levels				
CO_2	54.5809	1.8122	2.0399	−1.1507
	(0.8807)	(0.9650)	(0.9786)	(0.8751)
NO_x	82.5300	−1.4264*	−1.4060*	1.2459
	(0.1106)	(0.0769)	(0.0807)	(0.1064)
GDP	40.1424	2.3342	2.3140	−2.3888
	(0.9972)	(0.9902)	(0.9891)	(0.9915)
GDP^2	33.9751	3.0764	3.0231	−2.9176
	(0.9998)	(0.9990)	(0.9986)	(0.9982)
GDP^3	30.0662	3.1197	3.0910	−3.2528
	(1.0000)	(0.9991)	(0.9988)	(0.9994)
CREDIT	47.5849	1.7541	1.8680	−1.7506
	(0.9717)	(0.9603)	(0.9683)	(0.9600)
STOCK	34.7136	2.8141	2.7028	−2.8543
	(0.9997)	(0.9976)	(0.9962)	(0.9978)
BOND	59.1352	1.5266	1.3536	−0.7602
	(0.7698)	(0.9366)	(0.9111)	(0.7764)
FININDEX	89.283**	−0.1578	−0.6263	1.8032
	(0.0445)	(0.4373)	(0.2660)	(0.0357)
First differences				
$\Delta(CO_2)$	274.0547***	−11.1093***	−12.4977***	17.6690***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\Delta(NO_x)$	330.6820***	−13.1450***	−15.4935***	22.5248***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Δ(GDP)	190.9629***	−7.6048***	−8.2645***	10.5440***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
$\Delta(GDP)^2$	201.6362***	−7.4326***	−8.6094***	−11.4592***
	(0.000)	(0.000)	(0.0000)	(0.0000)
$\Delta(GDP)^3$	201.3489***	−7.2958***	−8.5385***	−11.4346***
	(0.000)	(0.000)	(0.0000)	(0.0000)
Δ(CREDIT)	114.5813***	−3.4850***	−3.4373***	3.9943***
	(0.0004)	(0.0002)	(0.0004)	(0.0000)
Δ(STOCK)	131.0578***	−5.1214***	−5.0516***	5.4072***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Δ(BOND)	445.7075***	−13.6313***	−20.3759***	−32.3882***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Δ(FININDEX)	227.9565***	−7.0913 ***	−9.4297 ***	13.7162 ***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)

Table 3. Fisher panel unit root tests
The number of lags has been set to two according to BIC. The statistics are the following: P is the inverse chi-squared statistic, Z is the inverse normal statistic and L^* denotes the inverse logit statistic, while P_m stands for the modified inversed chi-squared statistic. The augmented Dickey Fuller test is used rather than the Phillips-Perron test. The null hypothesis assumes that the variable contains a unit root. The numbers in parentheses denote the p-values. Significant at ***1% and *10% respectively

by Arellano and Bond (1991) *'can produce very misleading estimates of the average values of the parameters in dynamic panel data models unless the slope coefficients are in fact identical'*. Furthermore, the Arellano and Bond (1991) method performs well for $N > T$, which is the case in our data.[8]

[8]The DIF-GMM and SYS-GMM estimators were performed by using the STATA command *xtabond2* (Roodman, 2009).

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Equation	Statistic			
	G_τ	G_α	P_τ	P_α
$CO_2 = f$(GDP)	−2.603**	−11.211	−14.525***	−12.690***
	(0.037)	(0.727)	(0.005)	(0.000)
$CO_2 = f(\text{GDP})^2$	−2.738***	−11.328	−17.195***	−14.914***
	(0.003)	(0.691)	(0.000)	(0.000)
$CO_2 = f(\text{GDP})^3$	−2.738***	−11.328	−17.195***	−14.914***
	(0.003)	(0.691)	(0.000)	(0.000)
$CO_2 = f$(CREDIT)	−2.798***	−15.772***	−16.684***	−14.608***
	(0.001)	(0.000)	(0.000)	(0.000)
$CO_2 = f$(STOCK)	−2.766***	−13.619***	−15.426***	−11.306***
	(0.002)	(0.066)	(0.000)	(0.011)
$CO_2 = f$(BOND)	−2.767***	−12.324***	−15.098***	−12.435***
	(0.000)	(0.000)	(0.000)	(0.002)
$CO_2 = f$(FININDEX)	−2.470***	−7.616	−14.728***	−7.956***
	(0.000)	(0.328)	(0.000)	(0.000)
$NO_x = f$(GDP)	−3.203***	−14.590***	−18.539***	−13.855***
	(0.000)	(0.009)	(0.000)	(0.000)
$NO_x = f(\text{GDP})^2$	−3.261***	−15.506***	−20.211***	−15.910***
	(0.000)	(0.001)	(0.000)	(0.000)
$NO_x = f(\text{GDP})^3$	−3.282***	−16.281***	−21.045***	−16.891***
	(0.000)	(0.000)	(0.000)	(0.000)
$NO_x = f$(CREDIT)	−3.326***	−17.149***	−18.108***	−16.255***
	(0.000)	(0.000)	(0.000)	(0.000)
$NO_x = f$(STOCK)	−3.187***	−17.061***	−16.947***	−14.757***
	(0.000)	(0.000)	(0.000)	(0.000)
$NO_x = f$(BOND)	−3.556***	−17.467***	−17.098***	−15.125***
	(0.000)	(0.000)	(0.000)	(0.000)
$NO_x = f$(FININDEX)	−3.045***	−14.570***	−14.955***	−11.438***
	(0.000)	(0.010)	(0.001)	(0.008)

Table 4. Westerlund ECM panel cointegration tests
The test regression was fitted with a constant and trend and one lag and lead. The kernel bandwidth was set according to the rule $4(T/100)^{2/9}$ (Demetriades and James, 2011). The null hypothesis assumes that there is no cointegration. The numbers in parentheses denote the *p*-values. Significant at ***1% and **5% respectively

Table 5 presents the results from the static and dynamic model formulations for the case of the pollutants considered. In our case and in all specifications the signs of credit and bond are negative. More specifically, STOCK has the lowest magnitude in all cases and an opposite effect in comparison to bond. An N-shape relationship is observed in the static analysis for both pollutants, while in the dynamic analysis we still observe an N shape for the global pollutant and a monotonic relation for the local pollutant (see Figures 1 and 2).[9] We must mention that this finding contradicts the existing literature (Tamazian *et al.*, 2009; Tamazian and Rao, 2010; Nasreen *et al.*, 2017), where an inverted U shape is evident, leading to the acceptance of the EKC hypothesis. The reason for the existence of an N-shape relationship may be attributed to the different set of covariates used in the empirical specifications that combine macro-level data (GDP/capita) with micro-economic (banking and financial) variables (i.e. CREDIT, STOCK and BOND). Moreover, the advanced panel data econometric techniques to model the Kuznets curve using appropriate cointegration tests and addressing the existence of CD have redefined the standard EKC hypothesis.

Concerning the static specifications in all cases and for both pollutants, all explanatory variables are statistically significant and properly signed at all levels of significance. The calculated turning points are all within the sample

[9]Regarding the theoretical underpinnings justifying the existence of an N-shape relationship see Halkos 2013; 2012.

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	Static results					
Control variables	CO_2 Model 1 (MLE)	CO_2 Model 2 (MLE)	CO_2 Model 1 (GLS)	CO_2 Model 2 (GLS)	NO_x Model 1 (MLE)	NO_X Model 2 (MLE)
$CO_2(-1)$	–	–	–	–	–	–
NOx (−1)	–	–	–	–	–	–
GDP	0.000 453 9***	0.000 625***	0.000 458 3***	0.000 628***	0.000 031 8***	4.95×10^{-5}***
	(0.0000697)	(3.54×10^{-5})	(0.000 070 3)	(3.56×10^{-5})	(0.000 012 2)	(4.24×10^{-6})
GDP^2	-1.06×10^{-8}***	-1.42×10^{-8}***	-1.05×10^{-8}***	-1.43×10^{-8}***	-1.47×10^{-9}***	-1.74×10^{-9}***
	(1.71×10^{-9})	(9.15×10^{-10})	(1.73×10^{-9})	(9.21×10^{-10})	(2.95×10^{-10})	(1.09×10^{-10})
GDP^3	7.26×10^{-14}***	8.48×10^{-14}***	7.20×10^{-14}***	8.51×10^{-14}***	1.07×10^{-14}***	1.37×10^{-14}***
	(1.23×10^{-14})	7.27×10^{-15}	(1.25×10^{-14})	(7.33×10^{-15})	(2.12×10^{-15})	(8.67×10^{-16})
CREDIT	−0.009 497 1***	−0.001 96	−0.009 873 1***	−0.002 09	−0.001 875 9***	−0.002 29***
	(0.001 911 5)	(0.001 76)	(0. 001 926 3)	(0.001 77)	(0.000 328 5)	(0.000 210)
STOCK	0.006 983 4***	–	0.007 064 3***	–	0.000 963 6***	–
	(0.001 538 9)		(0.001 569 4)		(0.000 263 8)	
BOND	−0.179 284***	–	−0.177 170 6***	–	−0.019 384 9***	–
	(0.030 349 9)		(0.030 9601)		(0.005 195 6)	
Constant	4.683 581***	2.670***	4.492 349***	2.640***	1.174 816***	0.895***
	(1.076 7)	(0.832)	(1.011 429)	(0.707)	(0.215 046 1)	(0.138)
Diagnostics						
Turning points	65 539	81 486	64 144	82 042	79 058	66 583
	31 798	30 150	33 078	29 983	12 531	18 008
Shape of curve	N shape	N shape	N shape	N shape	N shape	N shape
LR test/*R*-squared	126.09*** [0.000]	461.87*** [0.000]	0.227	0.296	158.65*** [0.000]	945.49*** [0.000]
F-test	–	–	–	–	–	–
AR(1)	–	–	–	–	–	–
AR(2)	–	–	–	–	–	–
Hansen test	–	–	–	–	–	–

Table 5. Empirical results

+The one step estimators are reported. MLE denotes the GLS maximum likelihood estimator, GLS denotes the RE estimator, SYS-GMM is the system GMM estimator and DIF-GMM denotes the difference GMM estimator. Robust standard errors are in parentheses. The numbers in square brackets denote the *p*-values. The choice of FE was based on the Hausman test. AR(1) and AR(2) are tests for first and second order serial autocorrelation. LR test denotes the joint statistical significance of all the covariates. Hansen denotes the test of over-identifying restrictions of the instruments. Significant at ***1%, **5% and *10% respectively. The estimated peaks and lows are in constant USD at 2005 prices

with the upwards estimated points ranging from 64 144 USD to 65 539 USD in the case of CO_2 and 78 743 USD to 79 058 USD in the case of NO_x. In the case of CO_2 the downwards estimated turning points range from 31 798 USD to 31 078 USD and in the case of NO_x 12 531 USD to 14 206 USD. The magnitudes of the stock and credit are quite low while that for the bond is much higher and equal to approximately −0.18.

It is interesting to mention that the results are quite robust under different specifications. More specifically, as is evident from the relevant table the empirical results do not change significantly if we use only the credit variable (see Columns 3, 5, 7 and 9). As a consequence, the N-shape relationship between financial development and environmental degradation for local and global pollutants remains unaltered.[10]

[10]We reach the same conclusion for the dynamic models. To preserve space the dynamic results with the inclusion of the CREDIT variable are available upon request.

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	Static results	Dynamic results			
Control variables	NO_x Model 1 (GLS)	NO_x Model 2 (GLS)	CO_2 Model^{+} (DIF-GMM)	CO_2 Model (SYS-GMM)	NO_x Model^{+} (DIF-GMM)
$CO_2(-1)$	–	–	0.719*** (0.0509)	0.899*** (0.017 6)	–
NOx (−1)	–	–	–	–	0.314** (0.132)
GDP	0.000 034 9*** (0.000 012 3)	4.98×10^{-5}*** (4.25×10^{-6})	−0.000 512** (0.000 244)	0.000 18*** (6.51×10^{-5})	-1.23×10^{-5}*** (3.70×10^{-6})
GDP^2	-1.45×10^{-9}*** (3.02×10^{-10})	-1.75×10^{-9}*** (1.10×10^{-10})	1.24×10^{-8}* (6.52×10^{-9})	-4.75×10^{-9}*** (1.73×10^{-9})	–
GDP^3	1.04×10^{-14}*** (2.17×10^{-15})	1.37×10^{-14}*** (8.71×10^{-16})	-8.71×10^{-14}* (5.51×10^{-14})	3.47×10^{-14}*** (1.23×10^{-14})	–
CREDIT	−0.001 960 1*** (0.000 334 8)	−0.002 30*** (0.000 211)	−0.006 39*** (0.002 13)	−0.004 05** (0.001 63)	−0.002 92** (0.001 39)
STOCK	0.000 979 3*** (0.000 271 5)	–	0.002 48 (0.002 15)	0.003 70* (0.001 91)	0.001 18** (0.000 565)
BOND	−0.019 343*** (0.005 352 3)	–	–	–	–
Constant	1.077 573*** (0.190 714)	0.892*** (0.124)	0.719*** (0.050 9)	−0.739 (0.543)	–
Diagnostics					
Turning points	78 743 14 206	67 100 18 058	64 593 30 318	64 364 26 894	–
Shape of curve	N shape	N shape	Inverted N shape	N shape	monotonically decreasing
LR test/*R*-squared	0.320	0.511	–	4329.55*** [0.000]	–
F-test	–	–	105.78*** [0.000]	–	37.75*** [0.000]
AR(1)	–	–	−3.73*** [0.000]	−3.32*** [0.001]	−1.78 [0.074]
AR(2)	–	–	1.00 [0.319]	1.41 [0.160]	−0.33 [0.741]
Hansen test	–	–	29.68 [1.000]	28.49 [1.000]	32.16 [1.000]

Looking at the dynamic model specifications and especially in the DIF-GMM case for CO_2, GDP and its powers are statistically significant and only the financial variable CREDIT is significant, with the extraction of an inverted N-shape relationship with turning points within the sample and equal to 30 318 USD and 64 593 USD respectively. Similarly, in the case of system GMM for CO_2, GDP and its powers are statistically significant at all significance levels and now CREDIT is significant at 5% and STOCK at 10% levels, with the extraction of an N-shape relationship with turning points within the sample ranging from 26 894 USD to 64 364 USD.

Finally, in the case of DIF-GMM for NO_x, GDP is statistically significant and CREDIT and STOCK are significant at the 5% significance level, with a monotonically decreasing relationship of small magnitude. The adjustment coefficients are quite low in the case of CO_2, equal to 0.28 and 0.10 in the cases of difference and system GMM respectively, and higher in the case of NO_x (0.69 approximately).

Sensitivity Analysis

In order to check for the validity and robustness of our findings, we re-estimate our (static and dynamic) models of the main determinants of two major pollutants (CO_2 and NO_x emissions) on the basis of a different approximation. More specifically, we used the three banking variables (CREDIT, STOCK and BOND) to form a composite financial

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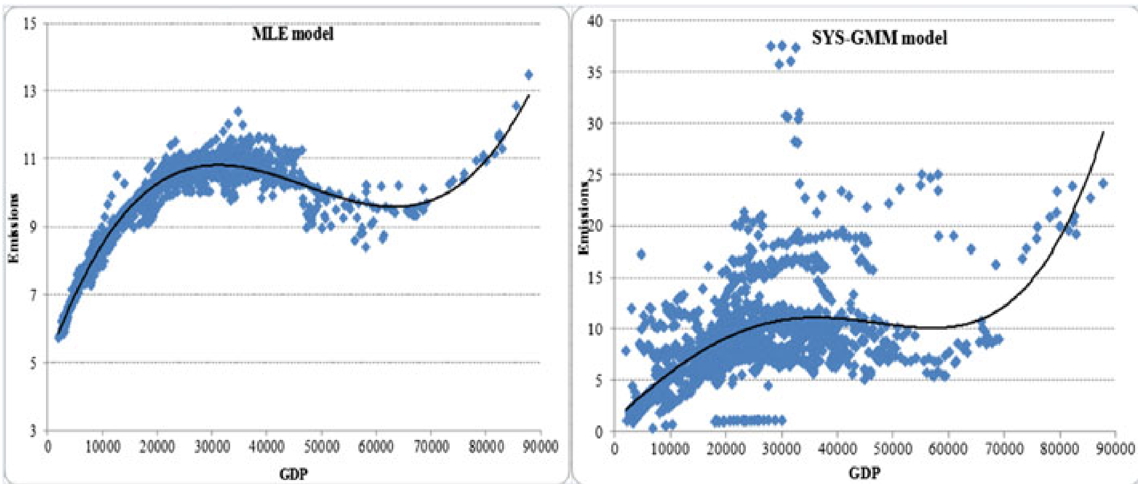
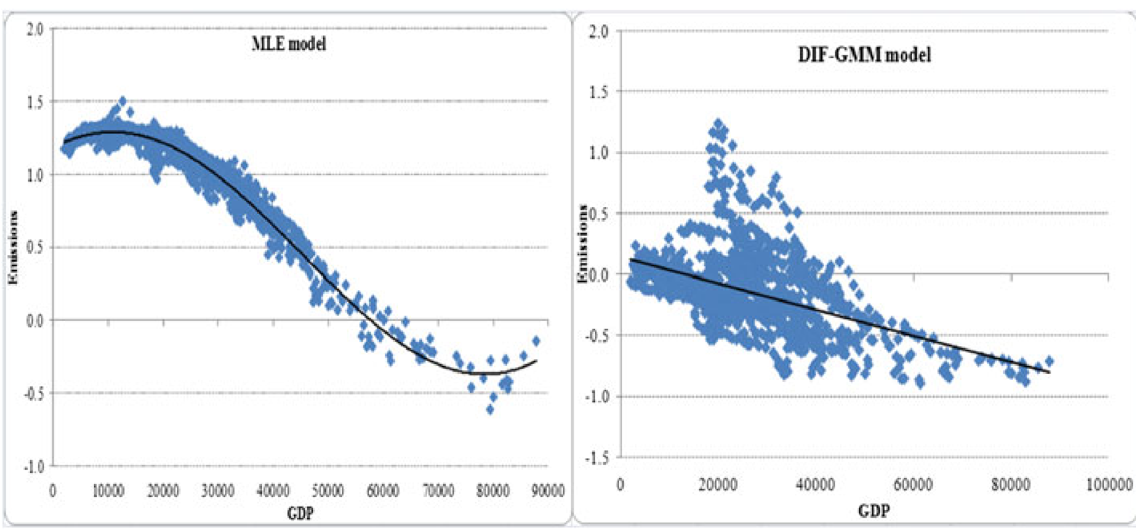


Note: MLE and SYS-GMM denote the (static) GLS maximum likelihood and (dynamic) System GMM model respectively. The graphs were constructed by multiplying GDP, GDP squared, GDP cubed by the sum of the estimated coefficients for current GDP. We normalized by adding to this the value of all the other banking development variables (CREDIT, STOCK and BOND) multiplied by their estimated corresponding coefficients and the constant term.

Figure 1. Influence of economic growth on CO_2 emissions [Colour figure can be viewed at wileyonlinelibrary.com]



Note: MLE and DIF-GMM denote the (static) GLS maximum likelihood and (dynamic) Difference GMM model respectively.The graphs were constructed by multiplying GDP, GDP squared, GDP cubed by the sum of the estimated coefficients for current GDP. We normalized by adding to this the value of all the other banking development variables (CREDIT, STOCK and BOND) multiplied by their estimated corresponding coefficients and the constant term.

Figure 2. Influence of economic growth on NO_x emissions [Colour figure can be viewed at wileyonlinelibrary.com]

index, denoted FININDEX.[11] The latter follows closely the spirit of Beck and Levine (2002), Luintel *et al.* (2008) and Antzoulatos *et al.* (2011), and is equal to the log ratio of the sum of stock market and private bond market capitalization divided by private bank credit. The main reason we incorporated the private bond market capitalization in the

[11]Other possible indexes may be market capitalization as a percentage of GDP, turnover ratio, liquid liabilities, domestic credit provided by the banking sector, or the value of share trade, each one as a share of GDP. According to Tyavambiza and Nyangara (2015), all these measures may provide biased results, as they are highly correlated and inappropriate to capture the financial sector's development potential.

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Control variables	Static results (1) CO_2 model (MLE)	(2) CO_2 model (GLS)	(3) NO_x model (MLE)	(4) NO_x model (GLS)	Dynamic results (5) CO_2 model$^+$ (DIF-GMM)	(6) CO_2 model (SYS-GMM)	(7) NO_x model (DIF-GMM)
$CO_2(-1)$	–	–	–	–	0.781^{***}	0.786^{***}	–
					(0.0378)	(0.0385)	
$NO_x(-1)$	–	–	–	–	–	–	0.491^{***}
							(0.0670)
GDP	$0.000\ 529^{***}$	$0.000\ 530^{***}$	$1.62 \times 10^{-5**}$	$1.72 \times 10^{-5***}$	$-0.000\ 460^{**}$	-0.000455^{**}	$-1.58 \times 10^{-5***}$
	(3.91×10^{-5})	(3.93×10^{-5})	(6.38×10^{-6})	(6.40×10^{-6})	(0.000 191)	(0.000196)	(5.12×10^{-6})
GDP^2	$-1.18 \times 10^{-8***}$	$-1.18 \times 10^{-8***}$	$-1.18 \times 10^{-9***}$	$-1.20 \times 10^{-9***}$	$1.05 \times 10^{-8**}$	$1.04 \times 10^{-8**}$	–
	(9.71×10^{-10})	(9.77×10^{-10})	(1.58×10^{-10})	(1.59×10^{-10})	(4.98×10^{-9})	(5.11×10^{-9})	
GDP^3	$7.05 \times 10^{-14***}$	$7.07 \times 10^{-14***}$	$1.07 \times 10^{-14***}$	$1.08 \times 10^{-14***}$	$-7.07 \times 10^{-14*}$	$-7.04 \times 10^{-14*}$	–
	(7.24×10^{-15})	(7.30×10^{-15})	(1.18×10^{-15})	(1.19×10^{-15})	(4.13×10^{-14})	(4.22×10^{-14})	
FININDEX	0.194^{***}	0.193^{***}	0.0219^{**}	0.0213^{**}	0.208^{**}	0.202^{**}	0.0195^{*}
	(0.052 2)	(0.052 7)	(0.008 50)	(0.008 57)	(0.0811)	(0.0807)	(0.0105)
Constant	3.512^{***}	3.485^{***}	1.215^{***}	1.203^{***}	–	–	–
	(0.834)	(0.745)	(0.157)	(0.138)			
Diagnostics							
Observations	986	986	988	988	949	949	954
Turning points	31 024	31 214	7 663	8 039	66 296	65 688	–
	80 560	80 054	65 857	66 035	32 714	32 797	
Shape of curve	N shape	N shape	N shape	N shape	inverted N shape	inverted N shape	monotonically decreasing
LR test/*R*-squared	280.53^{***} [0.000]	0.252	439.99^{***} [0.000]	0.376	–	–	–
F-test/Wald test	–	–	–	–	148.15^{***} [0.000]	682.94^{***} [0.000]	647.90^{***} [0.000]
AR(1)	–	–	–	–	-3.65^{***} [0.000]	−3.40 [0.001]	-1.33^{*} [0.098]
AR(2)	–	–	–	–	−0.77 [0.439]	−0.71 [0.476]	−0.34 [0.731]
Hansen test	–	–	–	–	32.70 [0.902]	32.70 [0.902]	30.36 [0.858]

Table 6. Sensitivity results

$^{(+)}$The one step estimators are reported. MLE denotes the GLS maximum likelihood estimator, GLS denotes the RE estimator, SYS-GMM is the system GMM estimator and DIF-GMM denotes the difference GMM estimator. Robust standard errors are in parentheses. The numbers in square brackets denote the p-values. AR(1) and AR(2) are tests for first and second order serial autocorrelation. LR and Wald tests denote the joint statistical significance of all the covariates. Hansen denotes the test of over-identifying restrictions of the instruments. Significant at ***1%, **5% and *10% respectively. The estimated peaks and lows are in constant USD at 2005 prices

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numerator of FININDEX is the fact that the aforementioned variable constitutes a major segment of the financial system in many countries (Beck *et al.*, 2001). An increase (decrease) of this index indicates a development (recession) of capital markets relative to the development of banks. This may increase (decrease) the level of environmental emissions in a country, which may lead to environmental degradation, justifying a call for further actions by policy makers and government officials (i.e. taxes, subsidies, tradable permits etc).

From the empirical results, it is evident that the main conclusions drawn in the previous section targeting the shape of the relationship between economic growth and financial development on pollution remain robust (see Table 6). More specifically, regarding the global pollutant (CO_2 emissions), we argue that in the static specifications (see Columns 1 and 2) an N-shape form is depicted, with very similar turning points ranging from 31 024 to 80 560 USD. The impact of financial development approximated by the FININDEX variable on environmental degradation as expressed by the level of CO_2 emissions is positive with its magnitude equal to 0.021 in both specifications. This means that if FININDEX increases (decreases) by 100% the level of per capita global pollutant will be increased (decreased) by 2.1%.

The same N-shape form is also evident in the case of local pollutant (NO_x emissions). Similarly, if financial and capital markets in the OECD countries show an increase (decrease) by about 100% the level of production and the subsequent NO_x concentrations emitted in the atmosphere will show a small increase (decrease), equal to approximately 2%.

Table 6 also presents the dynamic results obtained by this estimation process. It is worthwhile to mention that nearly all estimates are statistically significant with the appropriate sign. All underlying estimated equations pass a battery of diagnostic tests. Specifically, the instrument rank is greater than the number of estimated coefficients, while the reported Hansen test indicates that the instrument list satisfies the orthogonality conditions in all of the three specifications, since the null hypothesis that the over-identifying restrictions are valid cannot be rejected. Regarding the shape of the relationship in each of the three specifications, it is interesting to mention that the CO_2 models reveal a stable inverted N-shape relationship, in contrast to the NO_x model, where a monotonically linear decreasing approximation is evident (negative estimate of the GDP).

The most prominent outcome is the derivation of the long run effect of the FININDEX. As suggested by Polemis (2016), one of the main reasons for estimating a dynamic GMM model is to capture short run and long run effects. The long run effect is calculated as $1/(1 - \gamma)$ times the value for the coefficient of every independent variable, where γ is the estimated coefficient of the lagged dependent variable for each of the specifications. From the empirical findings, it is evident that the long run effect shows a different pattern on each of the two major pollutants. For example, in the case of the CO_2 models (see Table 6 Columns 5–7) this effect is almost five times greater than the short run effect of the first period based on Specifications (5) and (6) respectively, denoting that the level of CO_2 emissions will increase substantially in the long run (0.208 and 0.202 compared with 0.984 and 0.982 respectively). This result is reversed in the case of NO_x, where the long run effect of financial development is also positive but is almost 25 times greater in magnitude than the short run effect (0.0195 compared with 0.500). This means that financial integration causes some transient disruption to the level of NO_x emissions only in the short run, whilst the opposite holds in the long run. The different long run response rates between CO_2 and NO_x emissions (0.982–0.984 for CO_2 and 0.500 for NO_x) may be attributed to the geographical boundaries of the scrutinized pollutant (global versus local pollutant). In other words, CO_2, as one of the main greenhouse gases responsible for ‘global warming’, is a major global pollutant affecting all of the OECD countries and is more likely to demand faster response to financial evolution than NO_x emissions, acting at a local level (country or regions). Finally, it is worth mentioning that the long run effect of FININDEX on the level of CO_2 emissions is almost twice that in the case of local pollutant (NO_x emissions).

Conclusions and Policy Implications

Financial development plays a crucial role in determining the shape of the relationship between economic growth and the environment. In our analysis this relationship in the form of global (CO_2 emissions) and local (NO_x emissions) pollutants in both static and dynamic formulations was investigated. To explore these possible interactions we have considered the financial aspects both individually and as an index.

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The contribution of this paper is threefold. First, it thoroughly accounts for the presence of CD, where similar studies adopt a rather scant approach. Second, it utilizes the appropriate 'second generation' panel unit root tests in order to uncover possible cointegrated relationships, an issue that has been overlooked by the existing empirical literature on EKC. Third, and foremost, we thoroughly account for the interdependence between the financial development and economic growth under the presence of local and global pollutants.

From the empirical perspective, we argue that local and global pollutants redefine the validity of the EKC hypothesis when we account for the presence of financial development indicators. Moreover, it is evident that the shape of the relationship between growth and financial development on environmental degradation remains robust. Specifically, an N-shape relationship is observed in the static analysis for both pollutants, while in the dynamic analysis we have an N shape for the global pollutant but a monotonic relation in the case of the local pollutant. The calculated turning points are in all cases within the sample. The adjustment coefficients are very low for CO_2 emissions, ranging from 0.10 to 0.28, and very high in the case of NO_x emissions, almost equal to 0.7. In all specifications the signs of CREDIT and BOND are negative, with STOCK having the smallest magnitude and an opposite influence compared with BOND. The effect of financial development using as proxy the constructed financial index (FININDEX) on pollution in the form of CO_2 emissions is positive, with its magnitude equal to 0.021.

The long run effect presents different pictures for the two pollutants under consideration. For CO_2 the effect is five times larger compared with the short run effect of the first period, showing that long term the CO_2 emissions will substantially change. In contrast, for NO_x emissions the long run effect of financial development is again positive but much higher (almost 25 times greater in magnitude than the short run effect). This implies that financial integration may create transient disruption to NO_x emissions only short term, with the opposite being the case in the long term. This in turn shows that financial development in the banking sector is the cause of CO_2 and NO_x emissions, with financial development facilitating the installation of new more advanced and more cost-effective and energy efficient abatement methods as financial assistance may be obtained at lower cost. Finally, allocated financial resources have to ensure that credit will facilitate firms but not at the cost of environmental degradation.

These results could be important for policy makers, academic researchers and practitioners. More specifically, they call for a strengthening of the effectiveness of environmental degradation policies by ensuring sustainability of the OECD banking system in order to drastically reduce emissions. Moreover, policy makers and government officials have to stimulate investments in productive sectors such as the energy sector and more likely to promote the use of renewable energy sources. This can be accompanied by more financial resources for research and development and more cost effective mitigation methods.

Finally, when interpreting our empirical findings, some limitations have to be taken into consideration. Although we used several banking indicators to address the impact of financial development on environmental degradation, special attention should be paid to the use of additional (macro-economic) indicators such as the unemployment rate, the debt/GDP ratio, the level of public deficit etc. These measures affect the causality driven by the inclusion of financial indicators and reduce the possibility of endogeneity bias between the sample variables. Another limitation is the small sample size, which might be due to the fact that financial development indicators lack significant continuity among the OECD countries. Last, another alley for future research may be to include spatial aspects (i.e. geographical proximity) in order to uncover possible country differences and the sources of these different patterns.

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