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Environmental Kuznets Curve for the Informal Sector of Turkey (1950-2009)

Summary: In this study we investigate the empirical relationship between the size of the informal sector (as percentage of official GDP), carbon dioxide and sulfur dioxide emissions in Turkey by using annual data from 1950 to 2009 and conducting a time-series analysis using cointegration techniques. This analysis is crucial as pollution emissions may lead to unfavorable weather conditions and potentially cause environmental impacts that may adversely affect the global economy. The empirical analysis shows evidence towards the existence of an inverted-U relationship between relative informal sector size and environmental pollution indicators in the long-run. That is small and large sizes of the shadow economy are associated with little environmental pollution and medium levels of the size of the shadow economy are associated with higher levels of environmental pollution. Moreover, using multivariate cointegration techniques, we suggest and test an economic mechanism to account for this observation. This also helps us to prescribe various policy recommendations regarding pollution and energy use.

Key words: Informal economy, Error correction model, Cointegration, Greenhouse gas, Turkish economy.

JEL: E26, O17, Q53.

Informal sector, sometimes also referred to as black, shadow, hidden or underground economy is defined by Keith Hart (2008) as a set of economic activities that takes place outside the framework of bureaucratic public and private sector establishments. Yet another paper on the informal sector written by Jane Ihrig and Karina Moe (2004) defines it as a sector, which produces (mostly) legal goods, but does not comply with (most if not all of the) government regulations. Another definition is given by Vito Tanzi (1999), as the production and distribution of goods and services that are unaccounted for in the official National Income Accounts of a country. So all these definitions share the common feature in defining the informal sector that as opposed to formal sector is not regulated or observed by the government and therefore distorts efficient and adequate provision of government services (Gary A. Dymski 2013). Also see Friedrich G. Schneider and Dominik H. Enste (2000) for similar definitions of informality.

Environmental pollution is heavily dependent on the intensity of government regulations, overseeing and enforcement of environmental standards; therefore it would be a big mistake to overlook the presence of a shadow economy when analyzing environmental policy and outcomes. Moreover, as argued by Soham Baksi and

Pinaki Bose (2010), the presence of a large informal sector in developing countries indicates a serious challenge for the implementation of environmental regulations in these countries. Therefore, we believe that it is crucial to understand the association between informality and environmental performance.

To this end, in this paper we investigate the relationship between informal sector and environmental pollution/performance in Turkey using two different pollution indicators: CO_2 and SO_2 emissions *per capita*. We use annual data from 1950 to 2009 and the time series analysis we conduct provides evidence towards the existence of an inverted-U relationship between informal sector size and environmental pollution, i.e. the presence of an environmental Kuznets curve (EKC) relationship for the informal sector. Specifically, small and large sizes of the shadow economy are associated with little environmental pollution and medium levels of the size of the shadow economy are associated with higher levels of environmental pollution. To account for this non-linear relationship, we identify two channels through which informal sector might affect environmental pollution. We name the first channel as the scale effect through which larger (smaller) informal sector size is associated with lower (higher) level of environmental pollution. However, on the other hand there is also the deregulation effect of informality with which larger (smaller) informal sector size is associated with higher (lower) level of environmental pollution. As these two effects work in opposite directions the changing relative strength of one builds the inverted-U relationship between pollution indicators and informal sector size.

The rest of the paper is organized as follows. In Section 1, we provide a review of the existing literature on informality and pollution. Then, in Section 2 we lay out the theoretical framework, which provides the basis for the empirical relationship between informality and environmental performance. Next, in Section 3 we describe the dataset. In Section 4, we describe the methodological approach for the empirical analysis and present the estimation results. Finally, Section 5 provides some concluding remarks.

1. Literature Review

1.1 Empirical Literature

Environmental economics is a growing field of research as it especially attracted attention with the increasing focus of policymakers on environmentally sustainable development. For example, see Nathalie Homlong and Elisabeth Springler (2010) for the rising importance of the concept of sustainable development. Accordingly, taking measures towards reducing environmental pollution is one of the steps that has to be used by policymakers and governments to achieve a sustainable path for economic development.

As mentioned in the previous section, presence of an informal economy is a real challenge against achieving environmental goals. However, except a number of notable exceptions, papers in literature on the environmental impacts of informal sector are rare. This is due to the fact that time-series data of informal sector size for specific countries are not widely available. In that regard, the current paper aims to be the unique paper investigating the time-series relationship between pollution and informality from an aggregate perspective. In one study related to ours, Allen Blackman and Geoffrey J. Bannister (1998a) claim that in various developing countries the informal sector, which they argue that is comprised of low-technology unlicensed micro-enterprises, "... is a major source of pollution" and that "... environmental management in this sector is exceptionally challenging". In line with this study, Blackman and Bannister (1998b) argue that it is virtually impossible to regulate the informal sector with conventional tools. Furthermore, Blackman et al. (2006) make a similar argument and focus on the estimation of benefits of controlling informal sector emissions.

Moreover, we should also emphasize our paper's link to the well-developed literature on the EKC as this stream of literature, indicating the existence of a non-linear relationship between environmental pollution and formal output has been one of the sources of motivation for this paper. Among many others, in their seminal paper, Gene M. Grossman and Alan B. Krueger (1991) find an inverse-U shaped relationship, with a turning point within the sample, between SO_2, smoke and GDP. They explain these findings by "the changes in the scale of economic activity, composition of economic activity and techniques of production". Similarly, Theodore Panayotou (1997) finds an inverse-U relationship for SO_2 and GDP, and the results of his decomposition method show that the scale of economy and the share of industry positively affect the level of SO_2 positively while the effect of policies is negative. Moreover, Chien-Chiang Lee and Jun-De Lee (2009) apply unit root tests to *per capita* CO_2 emissions and real GDP *per capita*, and study the suitability of making a cointegration analysis between those variables. Maryam Asghari (2012) finds a similar U relationship between pollution and growth in Iran. Using a panel data vector error correction framework for six Central American countries, Nicholas Apergis and James E. Payne (2009) validate the existence of the EKC between CO_2 emissions and output. As much as the evidence in favor of its existence, there is also a large number of critics of the EKC hypothesis. To name a few, see Douglas Holtz-Eakin and Thomas M. Selden (1995), Sander M. de Bruyn, Jeroen C. J. M. van den Bergh, and Hans J. B. Opschoor (1998), Mariano Torras and James K. Boyce (1998) and Matthew A. Cole and Robert J. R. Elliott (2003) among many others for these criticisms.

Nevertheless, even though it is highly related to it, our main point in this paper is distinct from the EKC literature. The mechanism we highlight in this paper is novel compared to the hypothesized mechanism behind the EKC relationship. Moreover, as the relationship between informal sector size and income *per capita* is not a linear one, (see James E. Rauch 1993 and Kazuhiro Yuki 2007 for this observation) one cannot claim that the EKC hypothesis is the mechanism behind our observation.

As for the Turkish economy, empirical studies on the economics determinants and/or effects of pollution are various. Examples are Katalin K. Zaim (1999), Wietze Lise (2006), Elif Akbostanci, Serap Türüt-Aşık, and Ipek G. Tunç (2009), Ferda Halicioglu (2009) and Ugur Soytas and Ramazan Sari (2009), among many others. However, to the best of our knowledge there is no paper in the literature linking pollution to informality. One notable exception is a paper by Fatih Karanfil and Ata Ozkaya (2007) that builds a series of informal sector size in Turkey using environmental data. However, they do not focus on the informality-pollution relationship. Therefore, our paper is unique in analyzing the relationship between informality and pollution using a novel time-series data from Turkey.

1.2 Theoretical Literature

Among theoretical works related to the relationship between the informal sector and environmental pollution, a study by Sarbajit Chaudhuri (2005) builds a three-sector general equilibrium model with an informal sector and then uses this model to analyze the effects of different policies on environmental standards and welfare of the economy. In a somewhat related work Baksi and Bose (2010) analyze the effects of environmental regulation in the presence of an informal sector and find that stricter regulation can potentially increase or reduce pollution (or have a non-linear relationship with it). Sudeshna Chattopadhyay, Sarmilla Banerjee, and Katrin Millock (2010) are investigating a similar research question. These authors find that the usage of a Pigouvian tax might in fact foster informality and worsen environmental performance in a setting where formal and informal sectors have connections in the production process.

2. A Theoretical Framework

From a theoretical perspective, we hypothesize that the presence of an informal sector carries the potential to create two distinct effects on environmental pollution working in opposing directions. These are the deregulation and scale effects of informality. The next two subsections present these two effects in more detail.

2.1 Scale Effect of Informality

According to the empirical literature on informality, in contrast to the formal sector, the informal sector is highly labor-intensive, it mainly operates in small establishments, and uses less capital-intensive technology in order to avoid detection by the government authorities and possible tax payments or penalties (see Jean-Bernard Celestin 1989 and Ihrig and Moe 2004 for this argument). Also mentioned by Werner Antweiler, Brian R. Copeland, and M. Scott Taylor (2001), the low level of capital intensity and the small scale of production make the informal sector less prone to creating environmental pollution. Because of this mechanism, a larger (smaller) informal sector is expected to be associated with better (worse) environmental performance or smaller (larger) amounts of environmental pollution. Notice that this is an indirect effect of informality; as the size of the informal economy increases the capital intensity of the economy, which is positively related to pollutant emissions, decreases.

2.2 Deregulation Effect of Informality

By the generally accepted and widely used definition of the informal sector, it does not comply with most, if not all, of the government regulations. Surely, these regulations include environmental laws, rules, regulations and restrictions as well. Therefore, following this reasoning, a larger (smaller) informal sector is expected to be associated with a worse (better) environmental performance or larger (smaller) amount of environmental pollution. This can be interpreted as a direct effect of informality on pollution through an intrinsic factor of informal sector; absence of governmental regulation. Also, notice that the deregulation effect works in the opposite direction of the scale effect.

2.3 Accounting for the Inverted-U Relationship

These two distinct effects of informality, working in opposite directions carry the potential to create a non-linear U, or inverse-U, relationship between informality and environmental pollution if one effect is stronger than the other at some levels of the informal sector size and *vice versa* at other levels. To account for a possible non-linear relationship one might seek factors that create variation in the informal sector size. Two such factors are taxes and tax enforcement. If levels of taxes and tax enforcement create a variation in informal sector size and therefore capital intensity, then they might provide an account of a possible non-linear relationship in a multivariate framework. This is what we intend to do in the empirical analysis.

3. Data

To carry out the empirical analysis, we construct an annual time-series dataset for the Turkish economy running from 1950 to 2009.

In our empirical analysis we use CO_2 and SO_2 emissions as measures of environmental pollution. Notice that these are most widely used measures of environmental outcomes in the empirical literature. We obtained SO_2 emissions up to 2002 from David I. Stern (2005). Data for years after 2002 are obtained from Turkish Statistical Institute (TurkStat)[1]. Our data source for CO_2 emissions is mainly World Development Indicators of the World Bank[2] and United Nations Framework Convention on Climate Change (UNFCCC)[3]. Emissions data is in aggregate level nationwide and is measured in metric tons.

Our informal sector size estimates (in percentage of official GDP) are obtained from Ceyhun Elgin (2012) that uses a dynamic version of the multiple-indicators multiple-causes (MIMIC) model to provide annual estimates of the informal sector size in Turkey. Shortly, this method hypothesizes a list of indicators and causes of informality, connects these with informality using a structural equation model and then runs this model to back out informal sector size estimates. Notice that this method is widely used to estimate informal sector size in various countries. See Schneider and Enste (2000) and Schneider (2007) for a discussion. One of our motivations of using this particular dataset is that it is the one among its alternatives with

[1] **Turkish Statistical Institute - TurkStat.** 2011. http://www.turkstat.gov.tr/VeriBilgi.do?alt_id=10 (accessed December 5, 2011).
[2] **World Bank.** 2011. "World Data Bank - World Development Indicators." http://databank.worldbank.org/data/views/variableselection/selectvariables.aspx?source=world-development-indicators#c_e (accessed December 5, 2011).
[3] **United Nations Framework Convention on Climate Change - UNFCCC.** 2011. http://unfccc.int/ghg_data/items/3800.php (accessed December 5, 2011).

the longest time-series dimension (i.e. number of years). However, we also have conducted regressions some alternative informal sector series (albeit with shorter time-series span) and our results are qualitatively robust to incorporating these series into the analysis. These are available upon request from the corresponding author. One notable exception in this regard is the dataset provided by Elgin and Oğuz Öztunalı (2012) the time span of which for the Turkish economy is also the same as ours (i.e. from 1950 to 2009). Again, our results do not change qualitatively when we use this dataset. Moreover, also using informal sector size in *per capita* terms as an independent variable does not produce a qualitative change in our estimation results.

Finally, for the second pass of empirical analysis in the multivariate framework we use data on capital-output ratio, level of tax burden (tax revenue as % of GDP) and tax enforcement. Capital-output ratio data (denoted by *K*) is obtained from Deniz Çiçek and Elgin (2011) and constructed by using the perpetual inventory method. The series for tax burden is obtained from World Development Indicators of the World Bank and Organization for Economic Co-operation and Development (OECD) iLibrary databases[4]. For a proxy for tax enforcement (denoted by *E*) we follow the methodology also used by Ihrig and Moe (2004) using TurkStat data.

4. Methodological Approach and Empirical Findings

4.1 Methodological Approach

Our ultimate empirical purpose in this paper is to find out whether there is a long-run relationship between pollution and informal sector size. Moreover, provided that there exists such a relationship, we will investigate whether we can identify the factors behind it, specifically the two channels we named in the third section of the paper.

In line with these objectives and the fact that we are using annual time-series data, methodologically we will use the following procedures. First, we will test for the presence of unit root using three widely used tests: the augmented Dickey-Fuller (ADF) test suggested by David A. Dickey and Wayne A. Fuller (1979), the Phillips-Perron (PP) test developed by Peter C. B. Phillips and Pierre Perron (1988) and the Kwiatkowiski-Phillips-Schmidt-Shin (KPSS) test by Denis Kwiatkowski et al. (1992). Once we establish the existence of a unit root in the variables of interest, the second step will involve testing for cointegration using the Johansen technique *a la* Søren Johansen (1995). Once we can conclude that the variables are cointegrated we can run the causality tests based on an error correction model. Otherwise, if the Johansen procedure indicates that the variables are not cointegrated, the causality tests must be based on a Vector autoregression (VAR) model.

As well known, the Johansen technique is based on the estimation of cointegrating relationships between non-stationary variables using maximum likelihood estimation. The idea is to test for different distinct cointegrating vectors in a multivariate framework. For the purposes of this paper, this will be a three-dimensional VAR model in the following form:

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4 **Organisation for Economic Co-operation and Development - OECD.** 2011. http://www.oecd-ilibrary.org/statistics;jsessionid=1pcdbrnp18ec4.x-oecd-live-01(accessed December 5, 2011).

$$X_t = A_0 + A_1 X_{t-1} + A_2 X_{t-2} + ... + A_{p-1} X_{t-p+1} + u_t$$
$$X'_t = (\ln P_t, \ln IS_t, \ln IS^2_t). \qquad (1)$$

Here, $\ln P_t$ denotes the natural logarithm of *per capita* pollution emissions, $\ln IS_t$ denotes the natural logarithm of informal sector size relative to official GDP and u_t is a k x 1 vector of innovations. In error correction form, this equation transforms into the following:

$$\Delta X_t = A_0 + B_1 \Delta X_{t-1} + B_2 \Delta X_{t-2} + ... + B_{p-1} \Delta X_{t-p+1} + \pi X_{t-1} + v_t. \qquad (2)$$

According to this formulation, if π has reduced rank, that is $r < k$, then there exists $k \times r$ matrices λ and γ each with rank such that $\pi = \lambda\gamma'$ and $\gamma' X_t$ are stationary. Here, λ contains the adjustment parameters in the vector error correction model, each column in γ is a cointegrating vector and finally r is the number of cointegrating relationships.

Given the theoretical discussion above, the following long-run relationship between the relevant *per capita* pollution indicator P_t, either carbon dioxide or sulfur dioxide *per capita* emissions, and informal sector size relative to GDP, IS_t, is hypothesized:

$$P_t = \alpha_0 + \alpha_1 IS_t + \alpha_2 IS_t^2 + \sum_{k=3}^{n} \alpha_k X_k + \varepsilon_t. \qquad (3)$$

According to our theoretical hypothesis, the relative strength of the scale and deregulation effects will determine the signs of the estimates of α_1 and α_2.

4.2 Empirical Results

Table 1 presents results of the tests for the presence of unit roots in the data. As one can observe from the table, the variables are transformed into natural logarithm form before exposing them to unit root tests. Evidently, all of the three unit root tests yield a similar result that is all the variables are non-stationary in their levels. However, when first-differenced, they become stationary. Therefore, in this case it can be safely concluded that the level forms of all variables are integrated of order 1.

Next, after establishing the presence of unit root, the procedure proposed by Johansen (1995) is used to determine the number of cointegrating relationships. For this purpose, Table 2 presents the results of the Johansen cointegration test applied to $\ln P_t$, $\ln IS_t$ and $\ln IS_t^2$ where both sulfur dioxide and carbon dioxide *per capita* emissions are used for P_t. Both Akaike and Schwarz information criteria indicate that the optimal lag length is one. As both the trace and the maximum eigenvalue test statistics in Table 2 show, at the 5 percent level of significance, the results indicate that there is one cointegrating relationship for both pollution indicators.

Table 1 Unit Root Tests

Variables	ADF[a]		PP[a]		KPSS[b]	
	Constant	Constant and trend	Constant	Constant and trend	Constant	Constant and trend
lnCO_2	-1.23	-1.64	-1.43	-1.51	0.93***	0.22***
lnSO_2	-1.25	-0.87	-1.31	-1.15	0.74***	0.21**
lnIS	-2.47	-2.62	-2.16	-2.54	0.83***	0.21**
lnIS^2	-2.46	-2.61	-2.14	-2.48	0.85***	0.18**
ln$K$	-2.27	-3.08	-2.00	-2.89	0.77***	017**
ln$E$	-1.53	-1.35	-1.62	-1.45	0.69**	0.23***
lnTax	-1.33	-1.97	-1.27	-1.95	0.75***	0.17**
ΔlnCO_2	-7.75***	-6.63***	-7.83***	-8.38***	0.21	0.08
ΔlnSO_2	-5.99***	-6.12***	-5.99***	-6.10***	0.26	0.12
ΔlnIS	-6.86***	-6.83***	-5.82***	-5.95***	0.15	0.11
ΔlnIS^2	-7.06***	-7.04***	-5.87***	-6.36***	0.17	0.10
Δln$K$	-5.74***	-5.72***	-10.3***	-10.8***	0.19	0.11
Δln$E$	-7.56***	-7.85***	-7.53***	7.846***	0.15	0.08
ΔlnTax	-9.52***	-9.67***	-9.39***	9.676***	0.11	0.08

Notes: *, **, *** indicate 10, 5 and 1 percent level of significance, respectively.
a: H_0 = the series has unit root. AIC is used to select the lag length. The maximum number of lags is set to be ten;
b: H_0 = the series is stationary. Barlett Kernel is used as the estimation method and the bandwidth is selected with Newey-West method.

Source: Authors' calculations.

Table 2 Johansen Tests for CO_2 and SO_2 in Trivariate Case

	CO_2			SO_2		
Number of cointegrated equations	**r = 0**	**r ≤ 1**	**r ≤ 2**	**r = 0**	**r ≤ 1**	**r ≤ 2**
Trace statistic	31.558	9.520	1.673	52.729	13.080	2.633
Critical value[a]	29.797	15.494	3.841	29.797	15.494	3.841
Probability[b]	0.031	0.319	0.196	0.000	0.112	0.105
Maximum eigenvalue stat.	22.037	7.846	1.673	39.649	10.447	2.633
Critical value[a]	21.131	14.264	3.841	21.131	14.264	3.841
Probability[b]	0.037	0.394	0.196	0.000	0.184	0.105

Notes: a: Denotes rejection of the hypothesis at the 5 percent level of significance;
b: James G. MacKinnon, Alfred A. Haug, and Leo Michelis (1999) *p*-values.

Source: Authors' calculations.

Moreover, in line with the findings presented in Table 2, Table 3 presents the estimated cointegrating relationships along with the speed of adjustment coefficients for each pollutant emissions obtained from the three-dimensional vector autoregression model. Lagrange Multiplier and the joint Jarque-Bera test statistics are both satisfactory in both cases, that is the null hypothesis of no serial correlation at lag order 1 and the null hypothesis that residuals are multivariate are not rejected at 5 percent level of significance.

Table 3 Cointegrating Vectors in Trivariate Case

LM test statistic[a]	Joint Jarque-Bera test statistic[b]	Cointegrated equation	λ_i[c]
4.81	2.54	$\ln CO_2$ = 129.53 $\ln IS$ – 18.71 $\ln IS^2$ (21.55***) (3.04***)	-0.02 (0.01**)
9.96	2.99	$\ln SO_2$ = 100.55 $\ln IS$ – 14.49 $\ln IS^2$ (17.62**) (2.49**)	-0.05 (0.02**)

Notes: Number of observations is 60 and optimal lag length is 1. *, **, *** indicate 10, 5 and 1 percent level of significance respectively and figures in the parentheses indicate standard errors.
a: The null hypothesis of no serial correlation at lag order 1 is not rejected at the 5 percent level of significance;
b: The null hypothesis of residuals are multivariate normal is not rejected at the 5 percent level of significance;
c: The coefficients of the error correction term for each cointegrated equation.

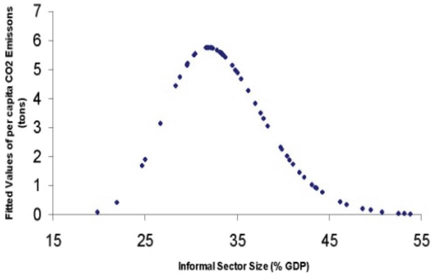
Source: Authors' calculations.

For the carbon dioxide model, the coefficients in the estimated long-run cointegrated equation are statistically significant at 1 percent level, whereas the coefficients are statistically significant at 5 percent level for the sulfur dioxide model. Moreover, from the signs of the estimates of α_1 and α_2 it can be observed that the data provides strong support in favor of an inverse-U shaped relationship between pollution emissions *per capita* and informal sector size relative to GDP. Specifically, the signs of the two estimates of α_1 are both positive and those of α_2 are negative. This indicates the existence of an inverted-U relationship between the two pollution indicators used in the analysis and informal sector size as percentage of official GDP.

Furthermore, the loading factor, which measures the speed of adjustment back to the long-run equilibrium level, is negative and significant, and provides support for the use of the error correction framework, that is the growth of pollution emissions are affected by the deviation from the long-run equilibrium.

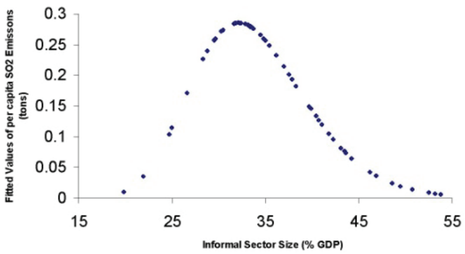
To visualize the inverted-U relationships, Figures 1 and 2 plot fitted values of *per capita* carbon dioxide and sulfur dioxide emissions against informal sector size as percentage of official GDP. In addition to the clearly identified inverse-U relationships, it can also be observed from Figures 1 and 2 that the peaks occur at around 31-32 percent, more specifically at 31.6 percent and 32.1 percent, respectively. Given the cointegrating relationship coming out of the empirical analysis, these are the points at which the pollution is maximized with respect to the size of the informal sector. Considering the most recent estimations of the informal sector size in Turkey which according to Elgin (2012) are all around 30% of GDP, we can safely argue that as of 2011, the Turkish economy is on the left of the maxima drawn in Figures 1 and 2. Therefore, it would be appropriate to argue that reducing informality would be associated with a reduction in pollution emissions as well.

Finally, in this subsection we also want to allow for the possibility of a cubic relationship between pollution and informality. That is, we want to check whether in addition to the squared-term, allowing for the cubic term of informal sector size would change the results of our analysis. Similar to the results presented in Table 2, at the 5 percent level of significance, the Johansen test results indicate that there is one cointegrating relationship for both pollution indicators. Given these results, we next estimate this cointegrating relationship and report the estimation in Table 4. We observe that the cointegrating relationship, estimated with the cubic term does not change the inverted-U relationship we obtained before. Specifically, the estimated coefficients of α_1 are still positive and those of α_2 are negative. Moreover, the cubic term does not have a significant coefficient.



Source: Authors' calculations.

Figure 1 Relationship between Carbon Dioxide Emissions and Informal Sector in Turkey



Source: Authors' calculations.

Figure 2 Relationship between Sulfur Dioxide Emissions and Informal Sector in Turkey

Table 4 Cointegrating Vectors in Trivariate Case, Cubic Model

LM test statistic[a]	Joint Jarque-Bera test statistic[b]	Cointegrated equation	λ_i[c]
2.01	2.04	$\ln CO_2 = 109.43 \ln S - 18.71 \ln S^2 + 0.45 \ln S^3$ (21.50***) (3.04***) (0.84)	-0.02 (0.01**)
5.76	2.08	$\ln SO_2 = 99.41 \ln S - 14.49 \ln S^2 + 1.02 \ln S^3$ (18.54**) (2.49**) (1.27)	-0.04 (0.02**)

Notes: Number of observations is 60 and optimal lag length is 1. *, **, *** indicate 10, 5 and 1 percent level of significance respectively and figures in the parentheses indicate standard errors.
a: The null hypothesis of no serial correlation at lag order 1 is not rejected at the 5 percent level of significance;
b: The null hypothesis of residuals are multivariate normal is not rejected at the 5 percent level of significance;
c: The coefficients of the error correction term for each cointegrated equation.

Source: Authors' calculations.

4.3 Multivariate Framework

In order to understand the underlying mechanism behind the inverted-U relationship and to see whether the theoretical mechanism that is provided in the third section of the paper holds or not, a further empirical analysis using the multivariate framework is conducted by checking the existence of cointegrating relationships between *per* *capita* pollution emission indicators lnCO_2 or lnSO_2 and lnIS, ln$K$, ln$E$ and lnTax, where K and E stand for capital-output ratio and tax enforcement.

The results of the Johansen cointegration tests in the multivariate framework are presented in Table 5. The Johansen tests indicate the presence of three cointegrating relationships at 5 percent significance level for both carbon dioxide and sulfur dioxide *per capita* emissions.

Table 5 Johansen Tests for CO_2 and SO_2, Multivariate Case

	CO_2			SO_2		
Number of cointegrated equations	**r = 0**	**r ≤ 1**	**r ≤ 2**	**r = 0**	**r ≤ 1**	**r ≤ 2**
Trace statistic	72.612	44.367	23.207	75.797	44.032	20.703
Critical value[a]	54.079	35.192	20.262	54.079	35.192	20.262
Probability[b]	0.001	0.003	0.019	0.000	0.004	0.043
Maximum eigenvalue stat.	29.391	23.070	18.155	31.765	23.329	15.982
Critical value[a]	28.588	22.299	15.892	28.588	22.299	15.892
Probability[b]	0.044	0.048	0.021	0.019	0.036	0.048

Notes: a: Denotes rejection of the hypothesis at the 5 percent level of significance;
b: Mackinnon, Haug, and Michelis (1999) *p*-values.

Source: Authors' calculations.

Table 6 reports the three estimated cointegrating relationships for each case. The cointegrating relationships clearly identify the two channels, namely the scale effect and the deregulation effect. The deregulation effect is represented by the positive sign of the estimated coefficient of lnIS in the first cointegrating relationship for both carbon dioxide and sulfur dioxide models. That is, through its direct effect on pollution, informal sector size and carbon dioxide or sulfur dioxide emissions *per capita* are positively correlated with each other. In the first cointegrating relationship, also a positive correlation between ln$K$ and emissions *per capita* can also be observed. The first cointegrating relationship which shows a positive correlation among capital intensity and pollutant emissions, together with the second cointegrating relationship which establishes a negative correlation between the capital intensity and the size of the shadow economy provides support for the existence of the scale effect of informality. Moreover, as for the left hand side variables of the second and third equations (i.e. lnTax and ln$E$) we observe that these are negatively correlated with informal sector size. Particularly, a higher level of tax burden and a higher degree of tax enforcement are associated with a smaller informal sector size. Considering the results presented in Elgin (2012) these findings are not surprising.

The results associate a larger (smaller) informal sector size with a higher level of pollution emissions *per capita* through its direct (deregulation) effect but with lower (higher) capital intensity. As capital intensity is significantly correlated with pollution emissions, the varying relative strength of each effect carries the potential to produce an inverted-U relationship between informal sector size and pollution in the case of Turkey.

Table 6 Cointegrating Vectors in Multivariate Case

LM test statistic[a]	Joint Jarque-Bera test statistic[b]	Cointegrated equation	λ_i[c]
30.100	7.477	lnCO_2 = 0.826 ln*IS* + 0.122 ln*K*	-0.257
		(0.186***) (0.960**)	(0.101***)
		ln*Tax* = -2.255 ln*IS* – 0.918 ln*K*	-0.194
		(0.309***) (0.322***)	(0.090**)
		ln*E* = -2.283 ln*IS* + 1.273 ln*K*	-0.154
		(0.341***) (0.799)	(0.075**)
19.396	4.275	lnSO_2 = 1.471 ln*IS* + 1.696 ln*K*	-0.321
		(0.391**) (0.560**)	(0.151**)
		ln*Tax* = -0.828 ln*IS* – 0.567 ln*K*	-0.105
		(0.372**) (0.122***)	(0.044**)
		ln*E* = -6.341 ln*IS* + 0.400 ln*K*	-0.064
		(1.493***) (1.556)	(0.031**)

Notes: Number of observations is 60 and optimal lag length is 1. *, **, *** indicate 10, 5 and 1 percent level of significance respectively and figures in the parentheses indicate standard errors.
a: The null hypothesis of no serial correlation at lag order 1 is not rejected at the 5 percent level of significance;
b: The null hypothesis of residuals are multivariate normal is not rejected at the 5 percent level of significance;
c: The coefficients of the error correction term for each cointegrated equation.

Source: Authors' calculations.

5. Concluding Remarks

In this paper, drawing motivation from the EKC literature, we analyze the relationship between the informal sector size and environmental performance (in terms of CO_2 and SO_2 emissions) of Turkey for 1950-2009 *via* cointegration analysis. The results of the trivariate cointegration analysis validate the existence of a unique long-run inverse-U shaped relationship among the emissions of both CO_2 and SO_2 and the size of informal sector. We also employ a multivariate cointegration analysis in order to investigate the two possible effects related to the informal sector. These are the scale effect and the deregulation effect, which may give rise to an inverse-U shaped relationship between pollutant emissions and the informal sector size. The results indicate a positive correlation between pollutant emissions and the informal sector size and therefore validate our identification of deregulation effect. Moreover, we also find evidence towards a negative correlation between capital intensity (which is positively correlated with emissions) and informal sector size, thereby confirming the existence of the scale effect. When these two effects work together, we obtain the inverted-U relationship. Moreover, we also find that the Turkish economy, which as of 2011 is estimated to have an informal economy size around 30% of GDP, is on the left side of the informal sector Kuznets curve. That is, in this side of the curve reducing informal sector size will be associated with a reduction in pollution emissions as well. Policy makers should take this into account when designing policies towards reducing environmental pollution. Specifically, reducing informality should be in the policy mix of any policy aiming environmentally sustainable development.

References

Akbostanci, Elif, Serap Türüt-Aşık, and Ipek G. Tunç. 2009. "The Relationship between Income and Environment in Turkey: Is there an Environmental Kuznets Curve?" *Energy Policy*, 37(3): 861-867.

Antweiler, Werner, Brian R. Copeland, and M. Scott Taylor. 2001. "Is Free Trade Good for the Environment?" *American Economic Review*, 91(4): 877-908.

Apergis, Nicholas, and James E. Payne. 2009. "CO_2 Emissions, Energy Usage, and Output in Central America." *Energy Policy*, 37(8): 3282-3286.

Asghari, Maryam. 2012. "Environmental Kuznets Curve and Growth Source in Iran." *Panoeconomicus*, 59(5): 609-623.

Baksi, Soham, and Pinaki Bose. 2010. "Environmental Regulation in the Presence of an Informal Sector." University of Winnipeg Department of Economics Working Paper 2010-03.

Blackman, Allen, and Geoffrey J. Bannister. 1998a. "Community Pressure and Clean Technology in the Informal Sector: An Econometric Analysis of the Adoption of Propane by Traditional Mexican Brickmakers." *Journal of Environmental Economics and Management*, 35(1): 1-21.

Blackman, Allen, and Geoffrey J. Bannister. 1998b. "Pollution Control in the Informal Sector: The Ciudad Juárez Brickmakers' Project." Resources for the Future Discussion Paper 98-15.

Blackman, Allen, Jhih-Shyang Shih, David Evans, Michael Batz, Stephen Newbold, and Joseph Cook. 2006. "The Benefits and Costs of Informal Sector Pollution Control: Mexican Brick Kilns." *Environment and Development Economics*, 11(5): 603-627.

Chattopadhyay, Sudeshna, Sarmilla Banerjee, and Katrin Millock. 2010. "Pollution Control Instruments in the Presence of an Informal Sector." Documents de travail du Centre d'Economie de la Sorbonne 10103.

Chaudhuri, Sarbajit. 2005. "Pollution and Welfare in the Presence of Informal Sector: Is there Any Trade-Off?" Economics Working Paper Archive 0510012.

Celestin, Jean-Bernard. 1989. *Urban Informal Sector Information: Needs and Methods*. Geneva: International Labour Office.

Çiçek, Deniz, and Ceyhun Elgin. 2011. "Not-Quite-Great Depressions of Turkey: A Quantitative Analysis of Economic Growth over 1968-2004." *Economic Modelling*, 28(6): 2691-2700.

Cole, Matthew A., and Robert J. R. Elliott. 2003. "Determining the Trade-Environment Composition Effect: The Role of Capital, Labor and Environmental Regulations." *Journal of Environmental Economics and Management*, 46(3): 363-383.

De Bruyn, Sander M., Jeroen C. J. M. van den Bergh, and Hans J. B. Opschoor. 1998. "Economic Growth and Emissions: Reconsidering the Empirical Basis of Environmental Kuznets Curves." *Ecological Economics*, 25(2): 161-175.

Dickey, David A., and Wayne A. Fuller. 1979. "Distribution of the Estimators for Autoregressive Time Series with a Unit Root." *Journal of American Statistical Association*, 74(366): 427-431.

Dymski, Gary A. 2013. "The Crisis of the Core Seen through the Eyes of the Periphery: A Schelling Model of the Global-South Megacity and the European Crisis." *Panoeconomicus*, 60(4): 433-455.

Elgin, Ceyhun. 2012. “Taxes and the Informal Sector: An Evaluation and the Case of Turkey.” *METU Studies in Development*, 39(2): 237-258.

Elgin, Ceyhun, and Oğuz Öztunalı. 2012. “Shadow Economies around the World: Model Based Estimates.” Bogazici University Department of Economics Working Paper 2012/05.

Grossman, Gene M., and Alan B. Krueger. 1991. “Environmental Impacts of a North American Free Trade Agreement.” National Bureau of Economic Research Working Paper 3914.

Halicioglu, Ferda. 2009. “An Econometric Study of CO_2 Emissions, Energy Consumption, Income and Foreign Trade in Turkey.” *Energy Policy*, 37(3): 1156-1164.

Hart, Keith. 2008. “Informal Economy.” In *The New Palgrave Dictionary of Economics. 2nd ed.*, ed. Steven N. Durlauf and Lawrence E. Blume, 176. Basingstoke: Palgrave Macmillan.

Holtz-Eakin, Douglas, and Thomas M. Selden. 1995. “Stoking the Fires? CO_2 Emissions and Economic Growth.” *Journal of Public Economics*, 57(1): 85-101.

Homlong, Nathalie, and Elisabeth Springler. 2010. “Economic Development and Foreign Direct Investment: How to Create Sustainable Development an Analysis of the Potential for Sustainable Development on the Indian Subcontinent.” *Panoeconomicus*, 57(3): 333-347.

Ihrig, Jane, and Karina Moe. 2004. “Lurking in the Shadows: The Informal Sector and Government Policy.” *Journal of Development Economics*, 73(2): 541-577.

Johansen, Søren. 1995. *Likelihood-Based Inference in Cointegrated Vector Autoregressive Models*. Oxford: Oxford University Press.

Karanfil, Fatih, and Ata Ozkaya. 2007. “Estimation of Real GDP and Unrecorded Economy in Turkey Based on Environmental Data.” *Energy Policy*, 35(10): 4902-4908.

Kwiatkowski, Denis, Peter C. B. Phillips, Peter Schmidt, and Yongcheol Shin. 1992. “Testing the Null Hypothesis of Stationary against the Alternative of a Unit Root.” *Journal of Econometrics*, 54(1-3): 159-178.

Lee, Chien-Chiang, and Jun-De Lee. 2009. “Income and CO_2 Emissions: Evidence from Panel Unit Root and Cointegration Tests.” *Energy Policy*, 37(2): 413-423.

Lise, Wietze. 2006. “Decomposition of CO_2 Emissions over 1980-2003 in Turkey.” *Energy Policy*, 34(14): 1841-1852.

MacKinnon, James G., Alfred A. Haug, and Leo Michelis. 1999. “Numerical Distribution Functions of Likelihood Ratio Tests for Cointegration.” *Journal of Applied Econometrics*, 14(5): 563-577.

Panayotou, Theodore. 1997. “Demystifying the Environmental Kuznets Curve: Turning a Black Box into a Policy Tool.” *Environment and Development Economics*, 2(4): 465-484.

Phillips, Peter C. B., and Pierre Perron. 1988. “Testing for a Unit Root in Time Series Regression.” *Biometrika*, 75(2): 335-346.

Rauch, James E. 1993. “Economic Development, Urban Underemployment, and Income Inequality.” *Canadian Journal of Economics*, 26(4): 901-918.

Schneider, Friedrich G., and Dominik H. Enste. 2000. “Shadow Economies: Sizes, Causes, and Consequences.” *Journal of Economic Literature*, 38(1): 77-114.

Schneider, Friedrich G. 2007. “Shadow Economies and Corruption all over the World: New Estimates for 145 Countries.” *Economics: The Open-Access, Open-Assessment E-Journal*, 1(9): 1-66.

Soytas, Ugur, and Ramazan Sari. 2009. "Energy Consumption, Economic Growth, and Carbon Emissions: Challenges Faced by an EU Candidate Member." *Ecological Economics*, 68(6): 1667-1675.

Stern, David I. 2005. "Global Sulfur Emissions from 1850 to 2000." *Chemosphere*, 58(2): 163-175.

Tanzi, Vito. 1999. "Uses and Abuses of Estimates of the Underground Economy." *Economic Journal*, 109(456): 338-347.

Torras, Mariano, and James K. Boyce. 1998. "Income, Inequality, and Pollution: A Reassessment of the Environmental Kuznets Curve." *Ecological Economics*, 25(2): 147-160.

Yuki, Kazuhiro. 2007. "Urbanization, Informal Sector, and Development." *Journal of Development Economics*, 84(1): 76-103.

Zaim, Katalin K. 1999. "Modified GDP through Health Cost Analysis of Air Pollution: The Case of Turkey." *Environmental Management*, 23(2): 271-277.