

Pollution, Shadow Economy and Corruption:
Theory and Evidence

Amit K. Biswas
Mohammad Reza Farzanegan
Marcel Thum

CESIFO WORKING PAPER NO. 3630
CATEGORY 9: RESOURCE AND ENVIRONMENT ECONOMICS
NOVEMBER 2011

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Pollution, Shadow Economy and Corruption: Theory and Evidence

Abstract

We study how the shadow economy affects pollution and how this effect depends on corruption levels in public administration. Production in the shadow economy allows firms to avoid environmental regulation policies; a large informal sector may be accompanied by higher pollution levels. Our theoretical model predicts that controlling the levels of corruption can limit the effect of the shadow economy on pollution. We use panel data covering the period from 1999–2005 from more than 100 countries to test this theoretical prediction. Our estimates confirm that the relationship between the shadow economy and the levels of pollution are dependent on the levels of corruption. Our results hold when we control for the effects of other determinants of pollution, time varying common shocks, country-fixed effects and various additional covariates.

JEL-Code: Q530, Q560, Q580.

Keywords: environmental pollution, shadow economy, corruption, panel data.

Amit K. Biswas
Faculty of Business and Economics
Technical University Dresden
Dresden / Germany
amit.biswas@mailbox.tu-dresden.de

Mohammad Reza Farzanegan
ZEW Mannheim
P.O. Box 103443
Germany – 68034 Mannheim
farzanegan@zew.de

Marcel Thum
Faculty of Business and Economics
Technical University Dresden & Ifo Dresden
Dresden / Germany
marcel.thum@tu-dresden.de

We are grateful to Peren Arin, Heike Auerswald, Caitlin Corrigan, Christian Lessmann and Gunther Markwardt for very helpful suggestions. We also wish to thank the participants of the European Public Choice Society conference (Izmir, 2010), 4th World Congress of Environmental and Resource Economists (Montreal, 2010), 11th IAEE European Conference (Vilnius, 2010), 67th Congress of the International Institute of Public Finance (Michigan, 2011) and brown bag seminars at the TU Dresden and ZEW Mannheim for their useful comments. The financial support of the Alexander von Humboldt foundation is highly appreciated.

1. Introduction

Water quality and air pollution have become serious problems in many developing countries. Human waste, fertilizers and industrial chemicals contaminate drinking water and cause significant health problems. According to the World Health Organization (WHO), water pollution is one of the main health risks and leads to approximately 2 million deaths annually. Air pollution causes about the same number of premature deaths worldwide per year. Pictures of megacities clouded by heavy fog, for instance, in China and Iran have appeared in newspapers around the world.¹ These problems are the negative effects of rapid growth driven by the extensive use of coal and fossil fuel.

Many of these environmental problems are fostered to a significant extent by the sizeable shadow economies in developing and emerging countries.² From 1999-2006, more than 50% of the overall GDP in Ukraine, Tanzania, Peru, Panama, Guatemala, Georgia and Bolivia originated in the shadow economy (Schneider et al., 2010). Between 1999 and 2006, the activity of shadow economies generated on average 34.5% of the official GDP in over 162 countries (Schneider et al., 2010).³ Figure 1 shows the average, minimum and maximum size of the shadow economy in the different regions.

The environmental hazards of the informal sector can be significant (Blackman, 2000). The shadow economy includes many pollution intensive activities, such as leather tanning, brick making, metal working, resource extraction, urban transportation with old and inefficient vehicles and production in small scale or family-based factories. In general, these firms do not follow environmental standards. The artisanal mining of gold, for example, uses mercury, which is discharged into rivers (Dondeyne et al., 2009). Bleaching, dyeing and tanning all produce dangerous chemicals, which can pollute rivers and groundwater (Baksi and Bose, 2010). Informal transportation in most developing countries is one of the main causes of local

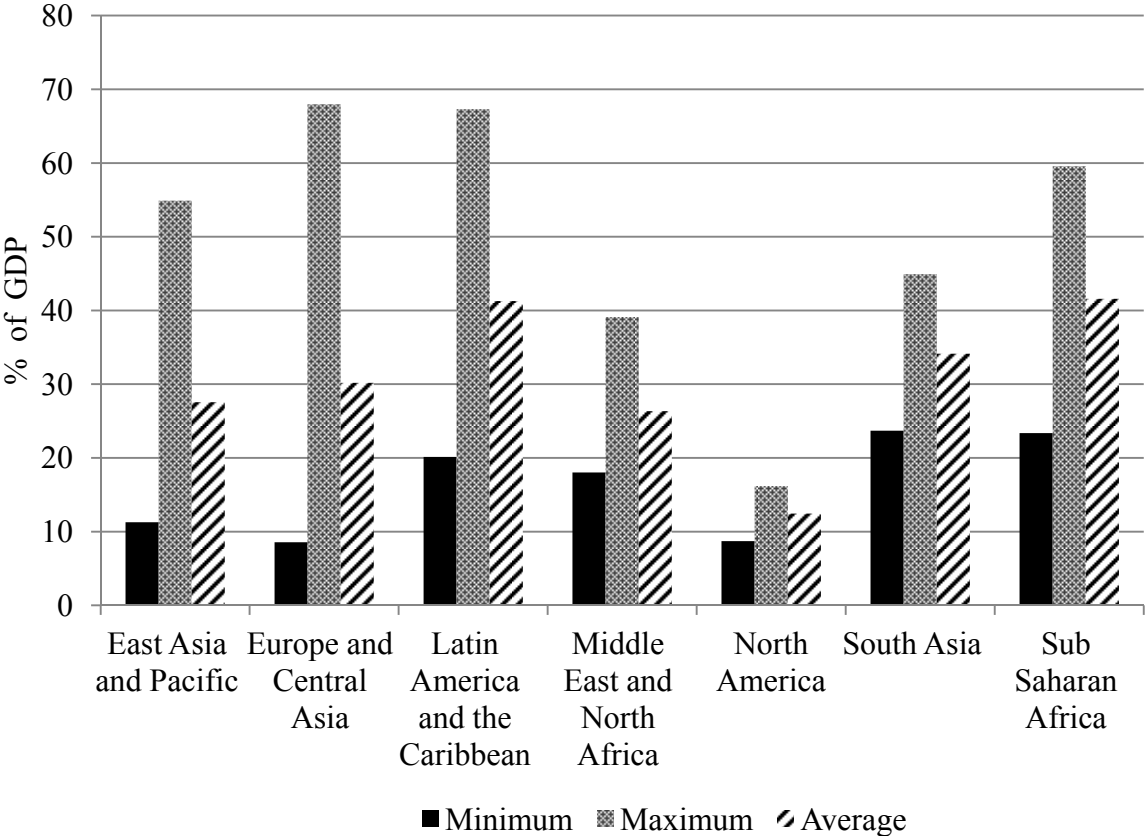
¹ Official Iranian sources report that approximately 10,000 people died due to the effects of pollution in 2005-06, calling living in Tehran a “collective suicide”. Approximately 70% of Tehran air pollution comes from the transport sector where the informal transport plays a major role. (See http://news.bbc.co.uk/2/hi/middle_east/6245463.stm).

² A common definition of the shadow economy is “all economic activities that contribute to the officially calculated (or observed) gross national product but are currently unregistered” (e.g., Feige 1994, Schneider 1994). For a survey of the shadow economies around the world, see Schneider and Enste (2000).

³ Employment in the informal economy is significant in many of these countries. More than 70% of all employment comes from the activity of the shadow economy in countries, such as Zambia (80.7%), Uganda (83.7%), Thailand (72.1%), Nepal (73.3%), Lithuania (72%), Ghana (78.5%) and Gambia (72.4%) (ILO, 2010).

air pollution (SO₂ emission). Vehicles in the informal transportation sector are usually old, poorly maintained and do not meet environmental quality standards.⁴

Figure 1. Size of the Shadow Economy (% of GDP) around the World (1999-2005)



Source: Schneider et al. (2010) and authors' calculations.

Surprisingly, there is still a lack of theoretical and empirical research on the shadow economy-environment nexus. A few theoretical studies (Baksi and Bose, 2010; Chaudhuri and Mukhopadhyay, 2006) analyze the effectiveness of environmental regulation on informal sectors. One of the key insights is that higher regulatory pressures may induce firms to shift more activities to the shadow economy.⁵ Unless governments fight the informal activities of shadow economies, they may not be able to implement effective environmental policies. Our model shows a similar effect of regulatory evasion. In addition, we account for the role of political and administrative corruption in the shadow economy-pollution nexus. Regulatory control is further weakened when economic agents in the informal economy can bribe corrupt

⁴ For more information on informal transport in developing countries, see a report by the UN-HABITAT at <http://www.unhabitat.org/pmss/listItemDetails.aspx?publicationID=1534>

⁵ Pollution leakage can also occur without the informal sector if environmental regulations differ between regions or sectors; see Copeland and Taylor (2003) and Fowlie (2009).

regulatory officials, which enables firms to continue their polluting activities in the shadow economy even after detection.⁶ We show that the destructive effects of the shadow economy are higher in countries with pervasive corruption. From a policy maker's perspective, fighting corruption may help to reduce the detrimental effects of the shadow economy on the environment.

In the literature, case and country studies provide evidence for the detrimental effects of the informal sector on pollution. For example, Blackman and Bannister (1998) and Blackman (2000) investigate the adaptation of propane by traditional brick makers in Mexico. Lahiri-Dutt (2004) examines informal mining in Asia and Biller (1994) describes the environmental hazards of informal gold mining in Brazil.⁷ What is missing in the literature is a comprehensive, cross-country analysis of informal sector activities and environmental pollution. In our empirical model, we test the extent to which the informal sector contributes to pollution and corruption undermines environmental policy.⁸ We use panel data covering the period from 1999-2005 for more than 100 countries. We find that the larger the shadow economy, the greater the pollution. However, this effect can be moderated by controlling corruption. Our results hold when we control for other major economic and demographic determinants of pollution, such as time varying common shocks, regional fixed effects and various additional covariates. We show the results for high-income and low-income countries separately to explore the possible differences between developed and developing countries.

The contributions of this paper are two-fold. First, we present a simple theoretical model that clearly demonstrates why we should expect the effect of the shadow economy on pollution to depend on the level of corruption. Second, we show that the theoretical effect of corruption on the shadow economy and pollution is empirically relevant. The remainder of the paper is structured as follows. Section 2 presents our theoretical model, which provides comparative statics that yield testable implications for subsequent analysis. Section 3 discusses our empirical strategy and the data. Section 4 presents the empirical evidence. Section 5 contains various tests of robustness and Section 6 concludes.

⁶ The direct link between corruption and pollution is discussed elsewhere; see Lopez and Mitra (2000) for a theoretical analysis and Pellegrini and Gerlagh (2006) or Welsch (2004) for empirical studies.

⁷ Veiga et al. (1994) point out that high mercury levels in the blood of fish-eating people in the Amazon are due to gold mining activities in the informal economy.

⁸ We discuss the literature on the determinants of pollution in Section 3.

2. The Model

This section develops a simple model of production with pollution, which can take place in the formal and informal sectors. Administrative corruption may allow firms in the informal sector to circumvent environmental regulations without being punished.

The output x of a representative firm can be produced in both the formal and informal sectors: $x = x_F + x_I$, where x_F and x_I are the outputs in the formal and informal sectors, respectively. The basic difference between these sectors is that the formal sector complies with all governmental regulations, while the informal sector can illegally bypass them. As production generates negative environmental externalities, the government tries to restrict and monitor the production of x . Without abatement, each unit of output x produces one unit of environmental pollution. The government sets the level of abatement $e \in [0,1]$. The case of $e = 0$ indicates no abatement. For $e = 1$, there is complete control of pollution. When governmental regulation is in place, the degree of pollution for each unit of output is $1-e$. For the firm, the effort to reduce pollution comes at a cost of $a(e)$ per unit of x (with $a' > 0$ and $a'' \geq 0$) along with the marginal cost of production. The production cost is given by $c(x)$ with $c'(x)$ and $c''(x) > 0$. The price of output is normalized to unity.

The cost of reducing pollution may tempt producers to move to informal production in the shadow economy. Shifting part of the production to the informal sector saves the producers the abatement costs on the amount of goods produced because the shadow economy does not require compliance with regulations. However, the government is aware of this possibility and monitors the production process. Thus, firms face the risk of detection. The probability of detection p depends on the size of informal production x_I . Therefore, $p = p(x_I)$ with $p' > 0, p'' \geq 0, p(0) = p'(0) = 0$.

However, not all monitoring officials are honest. In our model, the share of corrupt officials is γ . Once a firm's illegal pollution is detected, the subsequent punishment depends on the type of monitoring official. If the monitor is honest, the firm loses all of its informal output (x_I) and the penalty is $L = x_I$.⁹ However, if a dishonest producer meets a corrupt monitoring official, the firm can pay a bribe (b_I) to avoid legal consequences: $L = b_I$. The bribe will be determined by bilateral bargaining between the two parties.

⁹ We employ here a special punishment function because the firm loses all output in the informal sector. Note, however, that any function that links punishment to output and, in case of detection, reduces the net value below the outcome in the formal sector would lead to the same results.

To allow for different types of corruption, we assume that corrupt bureaucrats in the formal sector may also extort firms. If licenses are required in the formal economy, firms may have to bribe corrupt bureaucrats. We assume that a share of ψ of all bureaucrats in the formal economy is corrupt. If a firm meets a corrupt bureaucrat, it has to share its rent from formal production with the bureaucrat. The level of the bribe b_F is again determined by bilateral bargaining.

The timing of the two-stage game is as follows. In stage one, the firm decides on the amount of output to be produced formally and informally. In stage two, the output in the informal sector may be detected and the firm has to pay either the penalty or the bribe. To bring the output in the formal sector to the market, the firm may have to bribe an official. As usual, we solve the game by backward induction.

Stage 2: Average Penalty Costs and Bribes in the Formal Sector

As the representative entrepreneur is risk neutral, the firm has to consider the average penalty

$$EL = (1 - \gamma) \cdot x_I + \gamma \cdot b_I. \quad (1)$$

With some probability $(1-\gamma)$, the firm is detected by an honest official and pays $L = x_I$. With probability γ , the monitoring official is corrupt. In the case of the corrupt official, the equilibrium bribe b_I is determined through Nash bargaining. By making a bribe agreement, the firm avoids paying the penalty $L = x_I$. The impending penalty can be shared between the firm and the corrupt official. Hence, the Nash product is

$$\Omega_I = (x_I - b_I)^\alpha \cdot b_I^{1-\alpha}, \quad (2)$$

where α is the bargaining power of the firm.¹⁰ Maximizing (2) with respect to b_I and solving for the equilibrium bribe yields

$$b_I^* = (1 - \alpha) \cdot x_I. \quad (3)$$

The second order condition (SOC) is also satisfied. Substituting the equilibrium bribe, the average penalty cost (1) can now be written as

$$EL(x_I) = (1 - \gamma \cdot \alpha) \cdot x_I \quad (4)$$

This average penalty has to be paid when the cheating firm gets caught, which happens with probability $p(x_I)$.

¹⁰ The bargaining approach is common in the literature on corruption. The alternative approach is to allow the corrupt official to dictate the bribe [e.g., Shleifer and Vishny (1993), Choi and Thum (2004)]. In our case, a complete extraction of rents can be achieved by setting $\alpha = 0$.

The same bargaining procedure can be applied to determine bribes in the formal sector. The value of output in the formal sector amounts to x_F . Production costs and abatement costs are already sunk when the corrupt official makes his demands. The Nash product in the formal sector is

$$\Omega_F = (x_F - b_F)^\alpha \cdot b_F^{1-\alpha}.$$

Hence, the equilibrium bribe becomes

$$b_F^* = (1 - \alpha) \cdot x_F. \quad (5)$$

Stage 1: Production in the Formal and Informal Sectors

The firm maximizes its profit by choosing the total output of x and its division into formal and informal production¹¹

$$\pi = x_F + x_I - a(e) \cdot x_F - \psi \cdot b_F^* - p(x_I) \cdot EL(x_I) - c(x_F + x_I). \quad (6)$$

Total revenue amounts to $x_F + x_I$ and the firm faces four types of costs: the costs of regulating pollution, the expected bribe in the formal sector, the costs in the event of detection of informal production and the production costs. When we use the average penalty from Equation (4) and the bribe in the formal sector (5) and take the derivative, we obtain

$$\frac{\partial \pi}{\partial x_F} = 1 - a(e) - \psi \cdot (1 - \alpha) - c'(x) = 0 \text{ and} \quad (7)$$

$$\frac{\partial \pi}{\partial x_I} = 1 - (1 - \gamma \cdot \alpha) \cdot [p'(x_I) \cdot x_I + p(x_I)] - c'(x) = 0. \quad (8)$$

Combining Equations (7) and (8) yields

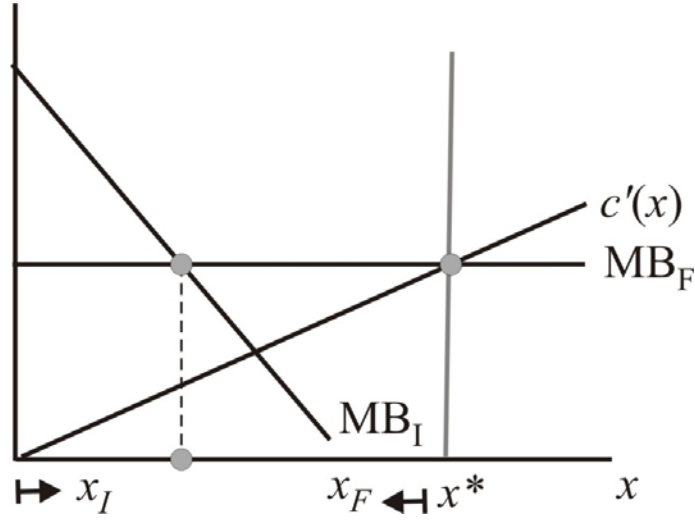
$$(1 - \gamma \cdot \alpha) \cdot [p'(x_I) \cdot x_I + p(x_I)] = a(e) + \psi \cdot (1 - \alpha). \quad (9)$$

Equation (7) describes the profit maximizing total output. The marginal revenue net of abatement and bribery costs has to be equal to the marginal cost of production.¹² Equation (9) shows that the profit maximizing division is achieved when the marginal abatement and bribery costs in the formal sector are equal to the marginal costs of detection in the informal sector. Figure 2 illustrates this outcome where total output is denoted on the horizontal axis. The firm's optimal output x^* is reached when the marginal cost of production (c') is equal to the net benefit from production in the formal sector ($MB_F = 1 - a(e) - \psi \cdot (1 - \alpha)$). The profit maximizing production in the informal sector is illustrated by the intersection of the net marginal benefit curves MB_F and $MB_I = 1 - (1 - \gamma \cdot \alpha) \cdot [p'(x_I) \cdot x_I + p(x_I)]$ of the formal and informal sectors, respectively.

¹¹ Throughout the paper, we assume that the bargaining power of the corrupt officials is sufficiently low that production in the formal and informal sectors remains profitable.

¹² For simplicity, we ignore the corner solution where all production takes place in the informal sector.

Figure 2. Profit Maximizing Production in the Formal and Informal Sectors



The comparative statics of the model reveal useful information about the impact of environmental regulation on output. The implicit differentiation of Equations (7) and (9) yields

$$\frac{dx^*}{de} = \frac{-a'}{c''(x^*)} < 0 \quad (10)$$

$$\frac{dx_I}{de} = \frac{a}{(1-\gamma \cdot \alpha) \cdot [2p'(x_I) + p''(x_I) \cdot x_I]} > 0. \quad (11)$$

Equations (10) and (11) depict the contrasting effects of increased regulatory measures on formal and informal production. When there is a tighter environmental regulation policy, total production (x^*) falls and informal production increases. Therefore, production in the formal sector must fall. In Figure 2, tighter regulation implies a downward shift of the MB_F curve.

Proposition 1. In the presence of an informal sector, tighter environmental regulation leads to a drop in output in the formal economy and an increase in activity in the shadow economy.

Emissions

Studying the impact of environmental regulation on emissions leads us to ask whether governments can improve environmental quality through regulatory measures when firms can escape regulation in the informal sector. Total emissions (E) are given by

$$E = x_I + (1 - e) \cdot x_F = (1 - e) \cdot x + e \cdot x_I. \quad (12)$$

The differentiation of Equation (12) with respect to e shows whether tighter regulations reduce emissions and improve environmental quality

$$\frac{\partial E}{\partial e} = -x_F + (1 - e) \cdot \frac{\partial x}{\partial e} + e \cdot \frac{\partial x_I}{\partial e} \quad (13)$$

The first two terms on the right-hand side are negative and the third term is positive [see Equations (10) and (11)]. The first two terms indicate that emissions fall because output drops and because each unit in the formal sector is produced with cleaner technology ($-x_F$). The negative effect emerges from the inframarginal units that are shifted to the informal sector, where they generate extra pollution, ε . This result leads to our second proposition.

Proposition 2. In the presence of an informal sector, the (marginal) introduction of environmental regulation ($e \approx 0$) reduces pollution. In general, the impact of tighter environmental regulation on emissions is ambiguous in the presence of an informal sector.

The Effect of Corruption on Environmental Quality

Finally, we examine two effects of corruption on environmental quality. First, corruption may affect the average penalty in the informal sector. Due to the rent sharing between corrupt officials and entrepreneurs, a larger share of corrupt officials increases the incentives for firms to move to the informal sector. The implicit differentiation of Equation (9) yields

$$\frac{dx_I}{d\gamma} = \frac{\alpha \cdot [p'(x_I) \cdot x_I + p(x_I)]}{(1-\gamma \cdot \alpha) \cdot [2 \cdot p'(x_I) + p''(x_I) \cdot x_I]} > 0. \quad (14)$$

Proposition 3. Increased corruption among the officials who monitor the informal sector expands the shadow economy. As total output (x^*) is not affected by the degree of corruption, total emission increases as informal production goes up.

Second, corruption may levy a burden on the formal sector. Therefore, we also analyze an increase in the share of corrupt officials ψ who demand payments for granting licenses. The differentiation of (9) yields

$$\frac{dx_I}{d\psi} = \frac{1-\alpha}{(1-\gamma \alpha) \cdot [2p' + p'' \cdot x_I]} > 0 \quad (15)$$

Hence, corruption in the formal sector also drives up informal activities [see also Choi and Thum (2005)]. Here, however, the net effect on environmental quality is ambiguous. Taking the derivative of (12) with respect to ψ and substituting (15) yields

$$\frac{\partial E}{\partial \psi} = (1 - \alpha) \cdot \left[\frac{e}{(1-\gamma \alpha) \cdot [2 \cdot p'(x_I) + p''(x_I) \cdot x_I]} - \frac{1-e}{c''} \right]. \quad (16)$$

While the first term in brackets is positive, the second term is negative. Again, for e close to zero, emissions fall when corruption increases. This result occurs because the negative effect of corruption on output dominates the shift in production.

Proposition 4. Increased corruption in the formal sector expands the shadow economy. Total output (x^*) falls with the degree of corruption, so the net effect on total emissions is ambiguous.

3. Empirical Strategy and Data

Based on our theoretical model, we formulate the following hypotheses:

H1: The shadow economy increases pollution.

H2: Corruption exacerbates the effect of the shadow economy on environmental degradation.

To test our hypotheses, we use fixed effects panel regressions. We begin by specifying that the dependent variable (pollution) is a linear function of our independent variables, such as the shadow economy. We then add further explanatory variables based on previous literature. To estimate whether the relationship between the shadow economy and pollution varies systematically with the level of corruption, we use the following model

$$em_{it} = cons + \beta_1 \cdot se_{it} + \beta_2 \cdot cor_{it} + \beta_3 \cdot (se_{it} \cdot cor_{it}) + \beta_4 \cdot Z_{it} + u_i + \theta_t + \varepsilon_{it}, \quad (17)$$

where the subscripts denote the country i and the time period t (1999-2005). em is the emission indicator and we use per capita SO₂ and CO₂ emissions alternatively. se is the share of the shadow economy in the GDP. cor is a proxy for the level of corruption and $se \cdot cor$ is the interaction term between the shadow economy and corruption. Finally, Z is a vector of control variables, such as energy efficiency, trade openness, population density, urbanization, working age population (15-64 years), education and quality of political institutions. Depending on the specification, the sample size varies between 107 and 134 countries.

The coefficient β_1 measures the marginal effect of the shadow economy (as % of the GDP) on pollution in the absence of corruption ($cor = 0$). Other factors, such as climate and geography, are country-specific and may correlate with pollution indicators. Because country-specific factors may cause the error terms to be correlated across all periods for a specific country or among countries for a particular year, pooled cross section estimates are inefficient (Selden and Song, 1994). In this case, the fixed-effect methods allow us to control for individual heterogeneity, which reduces the risk of biased results. We allow for country- (u_i) and time- (θ_t) fixed effects. The former captures unobservable time-invariant country characteristics and the latter captures shocks common to all countries. To determine whether fixed effects are superior to random effects, we perform the Hausman specification test (Hausman, 1978). This test rejects the null hypothesis of no correlation between the individual effects and the

explanatory variables at the 1% level ($p\text{-value} = 0$). This method suggests that fixed-effect models are more appropriate for our investigation than are random-effect regressions.¹³

The interaction term between the shadow economy and corruption captures the extent to which corruption increases or lowers the impact of the shadow economy on pollution. At the margin, the total effect of the shadow economy on pollution can be calculated by examining the partial derivative:

$$\frac{\partial (em_{it})}{\partial (se_{it})} = \beta_1 + \beta_3 cor_{it} \quad (18)$$

Thus, our coefficients of interest are β_1 and β_3 . We expect that β_1 is significantly positive (i.e., a larger informal sector increases pollution). Because corruption lowers the cost of shifting to the shadow economy, we expect to find a positive sign for β_3 as well.

Dependent Variable

The dependent variable is per capita environmental pollution. We employ the two most frequently used measures of air pollution in research: sulfur dioxide (SO₂) and carbon dioxide (CO₂).¹⁴

SO₂ per capita is a widely used indicator of local air pollution. SO₂ is the major cause of acid rain, which degrades trees, crops, water and soil.¹⁵ It also causes breathing problems, exacerbating asthma, chronic bronchitis and respiratory and cardiovascular disease. Smith et al. (2011) provide new estimates for global and regional anthropogenic sulfur dioxide emissions from 1850-2005. They estimate SO₂ emissions annually by country and from the following sources: coal combustion, petroleum combustion, natural gas processing and combustion, petroleum processing, biomass combustion, shipping bunker fuels, metal smelting, pulp and paper processing, other industrial processes and agricultural waste burning (AWB). Furthermore, SO₂ emissions are calculated annually for the following end-user sectors: energy, industry, transportation, domestic and agricultural waste burning (AWB). The end-use sectors are selected by Smith et al. (2010) for their standard reporting practice. The SO₂ emissions used in our estimates are the sum of SO₂ emissions from all of these sources for each country.

¹³ Hausman test results are available upon request.

¹⁴ We also examined the effect of the shadow economy on the organic water pollutant (measured by biochemical oxygen demand). The effect of the shadow economy is positive (increasing) and statistically significant. The results for BOD are available upon request.

¹⁵ <http://epi.yale.edu/Metrics/SulfurDioxideEmissions>

As an alternative indicator, we use (per capita) CO₂ emissions, which are a well-known cause of global warming.¹⁶ Our source of CO₂ emission information is the World Bank (2011). Carbon dioxide is generated by the consumption of solid, liquid and gas fuels and gas flaring. Therefore, CO₂ emissions are calculated primarily with the amount of energy consumption.

Independent Variables

The main independent variable is the share of the *shadow economy* in the GDP. Measuring the shadow economy is difficult because it is, by definition, hidden. The most common method is Multiple Indicators Multiple Causes (MIMIC) modeling, which is a kind of structural equation modeling.¹⁷ This method treats the shadow economy as a latent variable, quantifying its size based on the main causes and indicators of informal activity in the economy. We use the data from Schneider et al. (2010), who employ this method to estimate the size of the shadow economy for a number of countries in recent years (1999-2006/07).¹⁸ Appendix B presents a brief background on the methodology of shadow economy estimations. The advantage of structural equation modeling is that it allows us to address the measurement error problem. As Chang et al. (2009) note, “*the advantage of structural equation modeling over traditional regression analysis is that it explicitly models measurement errors and can estimate parameters with full information maximum likelihood (FIML), which provides consistent and asymptotically efficient estimates*”.

An alternative estimate for the size of informal economy across countries is provided by the World Economic Forum (Global Competitiveness Report 2005-2006 and 2006-2007). The size of the informal sector variable is constructed from a business survey by the World Economic Forum (WEF). The respondents were asked, “How much business activity in your country would you estimate to be unofficial or unregistered?” The variable is scaled from 0 to 100 percent. The correlation between the Schneider measure of the shadow economy and the WEF data is fairly high (0.73). The World Economic Forum (Global Competitiveness Report 2001/2002) also provides tax evasion data for a group of countries based on executives’

¹⁶ We prefer the SO₂ over the CO₂ measure for pollution because SO₂ generates local pollution. Hence, both the cost and benefits of environmental regulation accrue on the local level. The incentives for lower CO₂ emissions are less obvious and the costs of regulation are borne by the domestic economy. The benefits, however, accrue to the whole world because the reduction of greenhouse gas emissions is a contribution to a global public good. We report the results with CO₂ emissions as an alternative indicator because many other environmental studies focus on CO₂.

¹⁷ MIMIC models have also been applied to special facets of the shadow economy, such as smuggling (e.g., Farzanegan, 2009; Buehn and Farzanegan, 2012). For more details on the theoretical aspect of this methodology, see Bollen (1989).

¹⁸ These estimates have been used extensively in other empirical studies, such as Botero et al. (2004).

assessments of how important tax evasion is in their countries. Again, the correlation between the Schneider estimates and the tax evasion variable is quite high (-0.63). Therefore, we believe that the shadow economy measures of Schneider et al. (2010) are reasonable indicators for the size of the informal economy across countries and over time.

To measure corruption, we use the *corruption* index from the Political Risk Services (PRS). This index measures corruption in the political system and business related corruption, such as bribes connected to import and export licenses, exchange controls, tax assessments, or police protection. This index adequately captures the political and economic corruption described in our theoretical model. The PRS data has the advantage of covering many countries, thereby reducing the risk of a sample selection bias. This index of corruption is frequently used in the literature (e.g., Knack and Keefer, 1995; Alesina and Weder, 2002; Fredriksson and Svensson, 2003; and Bhattacharyya and Hodler, 2010). The original PRS corruption index varies from zero (most corrupt) to six (least corrupt). To interpret “increasing corruption,” we recode the index by subtracting the country scores from six such that higher values correspond with higher levels of corruption. For robustness analysis, we use the Corruption Perception Index of Transparency International. This index varies from zero (highest degree of corruption) to ten (least corruption). We transform this index such that higher scores indicate higher corruption. The CPI index is highly correlated with the actual experience of corruption, as measured by the International Crime Victim Survey data (Lambsdorff, 2007). Therefore, we are confident that measurement error is a minor issue with respect to corruption.

As an additional control variable, we use the *polity index* (Marshall et al., 2009) to measure democracy. Farzin and Bond (2006), for example, show that economic agents can implement their preferences for environmental quality more effectively in democracies than in autocratic societies.

We also control for other important determinants of air pollution. For example, increasing integration in the global economy and more *openness to trade* may play an important role in this issue. Cole (2004) suggests that trade openness may reduce pollution because countries have improved access to environmentally friendly technologies. However, the opposite effect can also occur. According to the pollution haven hypothesis, developed countries may export their dirty industries, such as the petrochemical and cement industries, to developing countries with lower environmental standards. In such a scenario, higher trade openness may increase environmental problems. As a measure of trade openness, we use the share of total trade

(imports+exports) in the GDP. In addition, the *sectoral structure of the economy* may influence pollution. In our general empirical specification, we control for the share of manufacturing production in the GDP. A higher share of value added in the industry and manufacturing may be accompanied by higher emissions (Dinda et al., 2000; Friedl and Getzner, 2003). We also account for the *efficiency of energy consumption*. Increasing energy efficiency implies a better use of energy. For a given level of production, improved energy efficiency will lead to decrease pollution. Efficiency is measured as GDP per unit of energy used.

We measure the following demographic variables: *population density*, the *share of urban population* in the total population and the percentage of the *total population in the age group from 15 to 64 years of age*. Urbanization may have mixed effects on the environment. On the one hand, increasing urbanization is associated with the intensive use of public and private transportation, thus increasing the consumption of fossil fuels (Panayotou, 1997). On the other hand, urbanization may facilitate citizen networking and NGO activities against industries that pollute heavily (see Rivera-Batiz, 2002; Torras and Boyce, 1998; and Farzin and Bond, 2006). Selden and Song (1994) show a negative effect of higher population density on the various indicators of pollution. They argue that sparsely populated countries have less incentive to reduce the emission per capita at every level of income. We also control for the level of education in our estimations. A more highly educated society is expected to be more aware of environmental hazards and related health problems (Pellegrini and Gerlagh, 2006; Farzin and Bond, 2006; and Bimonte, 2002). Scruggs (1998) shows that a higher level of education and wealth is associated with pro-environmental policies across all countries. As a proxy for the level of education, we use school enrollment rates (gross) at the secondary level. Finally, we use the share of the working-age population (15-64 years) as a demographic variable. Farzin and Bond (2006) discuss the different ways in which age composition influences environmental quality. They note that young people have a larger option value to wait for future improvements in environmental quality. In contrast, older people feel the health problems of pollution more directly and are willing to increase pressure on the government for stricter environmental regulation. However, older people may also be less willing to forego current consumption for future improvements in environmental quality.

Following Grossman and Krueger (1994), we control for the logarithm of *GDP per capita* (in current US dollars) and its square to account for the environmental Kuznets curve (EKC) hypothesis (for an overview of the EKC literature see Stern, 2004). As Schneider et al. (2010)

use GDP per capita as one of the causal variables of the shadow economy in their MIMIC models, the inclusion of GDP per capita alongside the shadow economy could inflate the standard errors of our estimates. The potential problem of omitted variables, such as historical legacies, culture and geographical characteristics, is mitigated by controlling for country and time-fixed effects. Appendix A lists all the variables and data sources. Table 1 reports the descriptive statistics of the major variables.

Table 1. Statistical Summary

Variable	Observations	Mean	Standard deviation	Minimum	Maximum
$\log(CO_2 \text{ per capita})$	1126	0.61	1.71	-4.39	4.82
$\log(SO_2 \text{ per capita})$	924	-11.43	1.38	-14.79	-8.48
$\log(\text{shadow})$	1119	3.44	0.44	2.12	4.24
$\text{corruption (rescaled)}$	973	3.31	1.21	0.00	6.00
$\log(\text{shadow}) * \text{corruption}$	930	11.44	4.87	0.00	24.23

4. Empirical Results

SO₂ Emissions as a Dependent Variable

We report the results with SO₂ emissions as the dependent variable. Table 2 presents several estimates for the nexus between the shadow economy and SO₂ emissions while controlling for country and time-fixed effects in all specifications. In column S.2.1, we start with a simple regression of the effects of the shadow economy and its interaction with corruption on SO₂ emissions. We observe an increasing and statistically significant effect of the shadow economy on SO₂ that increases at higher levels of corruption. However, this positive association may be driven by other omitted factors that influence both the shadow economy and local pollution. To address this issue, we follow the specific to general approach (see Herwartz, 2010 for more details) and add other important control variables in columns S.2.2-S.2.9. The positive (increasing) effect of the shadow economy on local pollution and the interaction term remain robust in all specifications. Our baseline regression is in column S.2.9, where we include all major variables. The coefficient of the shadow economy (*shadow*) is positive and statistically significant, as in the other models, and the coefficient of the interaction term is positive and statistically significant (at the 1% level). This result is in line

Table 2. Shadow Economy and SO₂ Emissions

Panel with fixed country and time effects (OLS)

	Dependent variable: SO ₂ emission (gigagrams (Gg) per capita)									
<i>Independent variables</i>	S.2.1	S.2.2	S.2.3	S.2.4	S.2.5	S.2.6	S.2.7	S.2.8	S.2.9	S.2.10
<i>shadow</i>	2.19*** (5.30)	2.37*** (4.60)	2.37*** (4.50)	2.36*** (4.35)	2.47*** (4.34)	2.30*** (4.08)	1.98 *** (3.35)	1.90*** (4.97)	1.47*** (3.15)	1.41*** (3.31)
<i>energy efficiency</i>		-0.30 ** (-1.99)	-0.39** (-2.49)	-0.39* ** (-3.96)	-0.41*** (-4.29)	-0.44*** (-3.98)	-0.55 *** (-3.76)	-0.58* (-1.78)	-0.58* (-1.86)	
<i>trade openness</i>			-0.06 (-1.30)	-0.06 (-1.18)	-0.06 (-1.18)	-0.10* (-1.67)	-0.11** (-2.01)	-0.02 (-0.43)	-0.03 (-0.38)	0.04 (0.58)
<i>population density</i>				-0.06 (-0.11)	-0.47 (-0.93)	-0.65 (-1.33)	-0.77 * (-1.75)	0.15 (0.31)	0.25 (0.41)	0.61 (0.77)
<i>urbanization</i>					1.59*** (11.49)	1.43*** (9.88)	1.77*** (16.49)	2.47*** (8.82)	3.19*** (7.15)	3.11*** (7.80)
<i>pop1564</i>						2.32*** (3.37)	2.45*** (3.84)	2.75*** (3.70)	1.98*** (2.64)	1.79** (2.08)
<i>polity</i>							-0.50* (-1.81)	-0.13 (-0.51)	-0.23 (-0.94)	-0.24 (-1.02)
<i>second_enrol</i>								-0.005*** (-3.36)	-0.005*** (-3.36)	-0.005*** (-3.55)
<i>corruption</i>	-0.22** (-5.80)	-0.27*** (-5.78)	-0.30*** (-5.52)	-0.30*** (-5.92)	-0.28*** (-6.22)	-0.32*** (-5.47)	-0.33*** (-5.54)	-0.37*** (-4.66)	-0.32*** (-4.16)	-0.22*** (-4.63)
<i>shadow*corruption</i>	0.07*** (7.17)	0.09*** (6.25)	0.09*** (5.92)	0.09*** (6.28)	0.09*** (6.80)	0.10*** (6.07)	0.10*** (6.33)	0.12*** (4.68)	0.10*** (4.73)	0.07*** (6.74)
<i>GDP p.c.</i>									0.55*** (2.68)	0.37** (2.46)
<i>GDP p.c.²</i>									-0.02** (-2.14)	-0.01 (-1.61)
<i>Manufacturing</i>									0.22** (2.06)	0.24** (1.96)
Adj. R ²	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97	0.97
Observations	818	803	783	783	783	783	735	646	613	625
Number of countries	118	116	115	115	115	115	109	108	105	107

Note: White robust *t*-statistics are in parentheses. Constant term is included (not reported). ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. 1 Gg = 1000 tons.

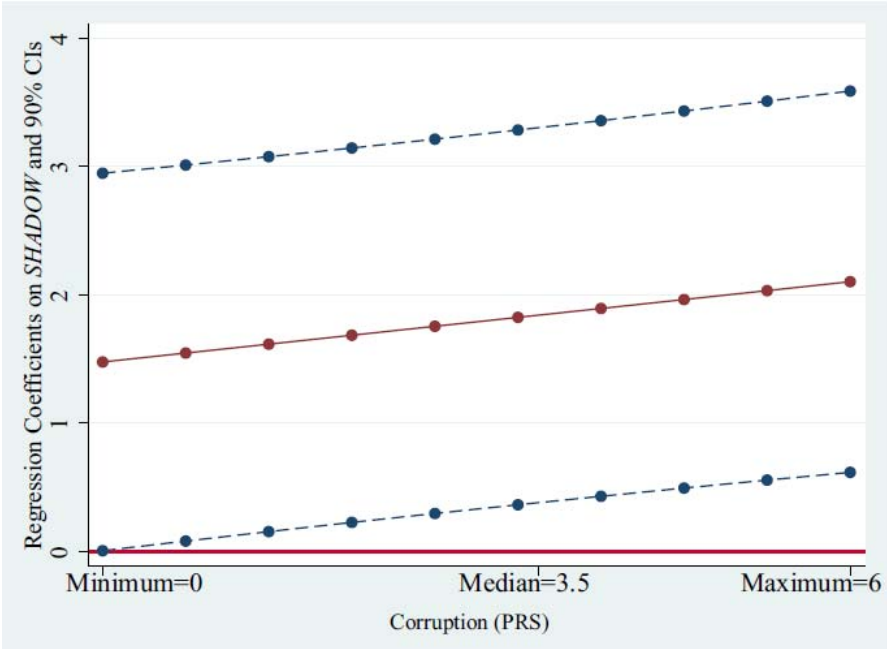
with our theoretical prediction that corruption amplifies the effect of the shadow economy on pollution. In other words, the control of corruption moderates the increasing effect of the shadow economy on SO₂ emissions. In column S.2.10, we exclude the energy efficiency variable from the model because it includes GDP and energy, which are determinants of emissions. Therefore, including the energy efficiency in our specification might overdetermine the estimation. However, as we can see from S.2.10, our main results of an increasing effect of the shadow economy and the amplifying effect of corruption remain robust. With respect to the environmental Kuznets curve, the results show that there is an inverted U-shaped relationship between income per capita and local (SO₂) emissions. These results are in line with the findings of Cole et al. (1997). However, having included the shadow economy variable, we should be cautious in interpreting the coefficient of the income variables because there is a relatively high correlation between the logarithm of the GDP per capita and the logarithm of the shadow economy (-0.68).

To improve our impression of the total effect (including the indirect effect via corruption), we calculate the marginal effect of a 1% increase in the size of the shadow economy on local pollution at different levels of corruption (based on S.2.9 in Table 2). The results are reported in Figure 3. In the absence of corruption, a 1% increase in the size of shadow economy increases SO₂ emissions by 1.47%. At the maximum level of corruption, SO₂ emissions increase by 2.07%. Therefore, SO₂ emissions increase by 40.8% when corruption increases from zero to its maximum score of six. These marginal effects are statistically significant at the 10% level, as shown by the dashed lines for the confidence intervals. This result suggests that controlling corruption significantly moderates the destructive effects of the shadow economy on local air pollution.

Furthermore, other variables are statistically significant in almost all the specifications. For example, higher education (secondary school enrollment) significantly reduces the SO₂ emissions per capita (see columns S.2.8-S.2.10). This finding is in line with Scruggs (1998), Bimonte (2002), Rivera-Batiz (2002) and Farzin and Bond (2006). Another statistically significant variable with a negative effect on local air pollution is energy efficiency (measured as the GDP divided by energy consumption). Countries with more efficient production technologies can reduce the energy intensity of their industries and reduce the total local air pollution. We also find evidence that a higher proportion of a working age population (15 to 64 years) increases local environmental pressures (see Columns S.2.6-S.2.10). When a high share of the population is working age, there is a large labor force, which is a necessary input

for production. This demographic shift towards a working age population may feed activities in both the formal and the shadow economy, which leads to increases in environmental pollution.

Figure 3. Marginal Effects of the *Shadow Economy* on SO₂ Emissions per capita (using S.2.9 in Table 2)

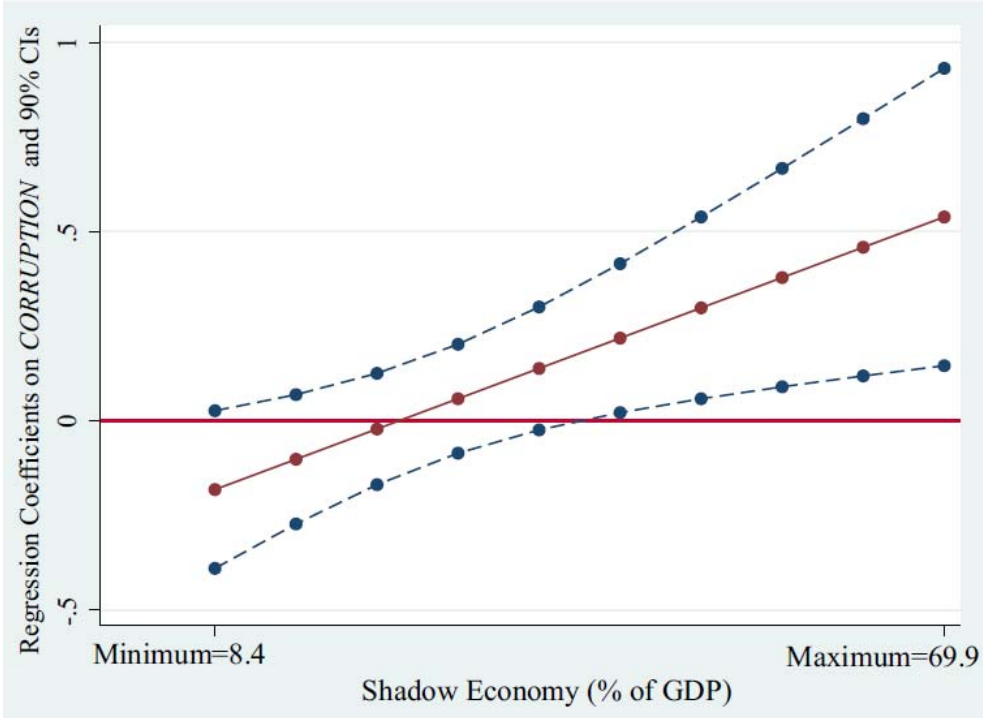


Note: The middle solid line shows the marginal impact of a 1% increase in the size of the shadow economy on SO₂ emission per capita at different levels of corruption. The dashed lines are 90% confidence intervals (CIs).

Another observation is the negative direct effect of corruption on pollution. Our theoretical model is not conclusive on the total effect of corruption on pollution. Proposition 4 states that the net effect of corruption on emissions is ambiguous. Corruption can increase pollution by affecting the stringency of environmental regulation and enforcement. However, corruption also has a negative impact on pollution by lowering economic activity (for the negative effect of corruption on growth, see Mauro, 1995, Knack and Keefer, 1995; Tanzi and Davoodi, 2001; and Mo, 2001, among others). Cole (2007) evaluates the magnitude of these two countervailing effects of corruption on pollution and shows that, for the majority of countries, the negative effect of corruption outweighs the positive impact on pollution. In our setting, the final effect of corruption on pollution varies at different levels of the shadow economy. Our estimations show that the marginal impact of an increase in corruption on SO₂ emissions is significantly positive when the size of the shadow economy is above the sample average. A 1% increase in the corruption index increases the SO₂ pollution per capita by 0.1% and 0.5% at the mean and maximum size of the shadow economy. Given a sizable shadow economy, higher corruption allows informal firms to continue their operations by bribing monitoring

bureaucrats, thus allowing the emission of more pollution. When the shadow economy is of a negligible size, the effect of higher corruption on local pollution is negative (-0.2%) but not statistically significant, as observed from the confidence intervals in Figure 4.

Figure 4. Marginal Effects of Corruption on SO₂ Emissions per capita (using S.2.9 in Table 2)



Note: The middle solid line shows the marginal impact of a 1% increase in the level of corruption on SO₂ emission per capita at different levels of the shadow economy. The dashed lines are 90% confidence intervals (CIs). Note that, for expositional purposes, we use a logarithm of corruption and that the shadow economy is shown in terms of the share of the GDP.

CO₂ Emissions as a Dependent Variable

In line with our results for SO₂, we notice a significantly positive and direct effect of the shadow economy on CO₂ emissions per capita in all specifications (Table 3). In the baseline model (column S.3.9), a 1% increase in the size of the shadow economy increases CO₂ emissions per capita by 1.41% in the absence of corruption. Similar to our SO₂ models, the increasing effect of the shadow economy on CO₂ emissions is dependent on the level of corruption. The interaction term between the shadow economy and the corruption index is significantly positive; corruption amplifies the effect of the shadow economy on CO₂ emissions.

Table 3. Shadow Economy and CO₂ Emissions

Panel with fixed country and time effects (OLS)

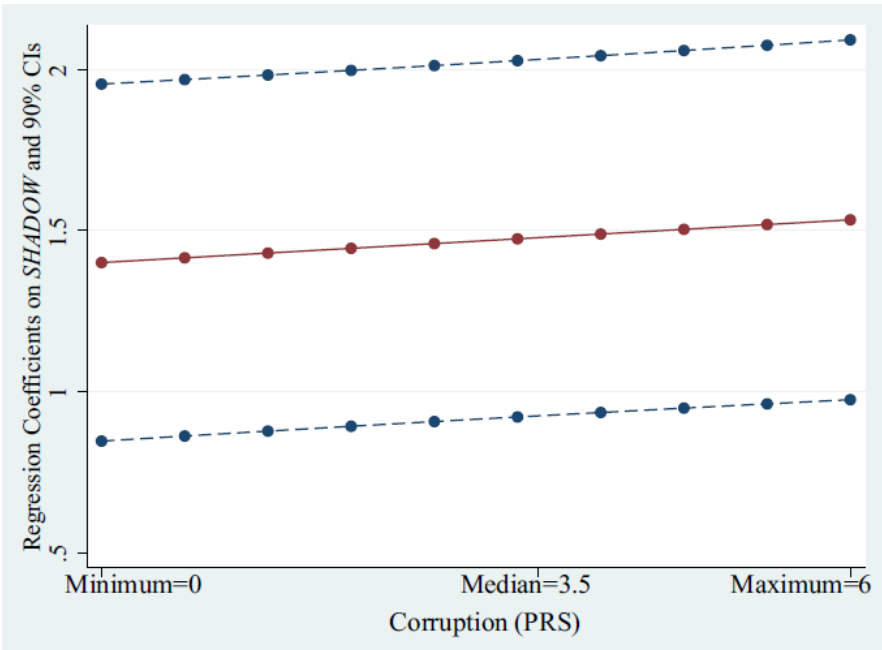
<i>Independent variables</i>	Dependent variable: CO₂ emission (metric tons per capita)									
	S.3.1	S.3.2	S.3.3	S.3.4	S.3.5	S.3.6	S.3.7	S.3.8	S.3.9	S.3.10
<i>shadow</i>	1.40 *** (4.10)	1.95*** (4.88)	1.92*** (4.76)	1.89*** (4.79)	1.97*** (5.70)	1.91*** (5.43)	1.82*** (5.52)	1.74*** (4.16)	1.41** (2.32)	1.26*** (2.82)
<i>energy efficiency</i>		-0.54*** (-8.17)	-0.55*** (-8.11)	-0.59*** (-7.90)	-0.60*** (-8.49)	-0.61*** (-9.93)	-0.55*** (-7.27)	-0.54*** (-6.42)	-0.59*** (-9.36)	
<i>trade openness</i>			-0.01 (-0.40)	-0.01 (-0.37)	-0.01 (-0.49)	-0.03 (0.83)	-0.02 (-0.48)	-0.03 (-0.83)	-0.01 (-0.38)	0.07*** (2.67)
<i>population density</i>				-0.30 (-1.31)	-0.78*** (-3.16)	-0.86*** (-4.01)	-0.79*** (-3.76)	-0.76*** (-3.39)	-0.46* (-1.87)	-0.27 (-1.08)
<i>urbanization</i>					1.88*** (15.65)	1.82*** (14.62)	1.85*** (12.55)	1.92*** (12.81)	1.54*** (11.89)	1.38*** (6.15)
<i>pop1564</i>						0.88** (2.42)	0.84** (2.05)	1.57*** (4.40)	1.09* (1.89)	1.03*** (3.37)
<i>polity</i>							-0.24*** (-3.54)	-0.22** (-2.36)	-0.24*** (-3.23)	-0.24*** (-3.55)
<i>second_enrol</i>								-0.0004 (-0.43)	-0.0009 (-0.90)	-0.0002 (-0.32)
<i>corruption</i>	-0.002 (-0.11)	-0.05** (-2.43)	-0.06*** (-2.73)	-0.07*** (-2.78)	-0.05** (-2.30)	-0.06*** (-2.78)	-0.07*** (-3.30)	-0.11*** (-3.02)	-0.08* (-1.78)	-0.02 (-0.62)
<i>shadow*corruption</i>	0.001 (0.28)	0.01*** (2.33)	0.02*** (2.60)	0.02*** (2.62)	0.01** (2.15)	0.01*** (2.51)	0.02*** (3.01)	0.03*** (2.81)	0.02* (1.69)	0.009 (0.68)
<i>gdp p.c.</i>									0.23 (1.31)	-0.16 (-0.97)
<i>gdp p.c.²</i>									-0.007 (-0.76)	0.01 (1.45)
<i>manufacturing</i>									0.12*** (3.83)	0.15*** (7.56)
Adj. R ²	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99	0.99
Observations	797	694	678	678	678	678	636	565	537	698
Number of countries	134	117	116	116	116	116	109	108	104	118

Note: White robust *t*-statistics are in parentheses. Constant term is included (not reported). ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

As for the SO₂ models, we can calculate the effect of a 1% increase in the size of the shadow economy at different levels of corruption. The results are illustrated in Figure 5. At the minimum, mean and maximum level of corruption, a 1% increase in the shadow economy increases CO₂ emission per capita by 1.41, 1.70 and 1.95%, respectively. Again, the final effect of the shadow economy on CO₂ emissions is positive and the control of corruption moderates this increasing effect. As shown by the confidence intervals (dashed lines), the total effect is significant at 10% for all levels of corruption.

Several other variables are significant throughout most of the specifications. Higher urbanization and a larger share of the working age population significantly increase CO₂ emissions per capita and higher energy efficiency reduces emissions. In contrast to the SO₂ estimates, population density is a significant factor in the reduction of CO₂ emissions. Education plays no significant role in our CO₂ emission models. It seems that higher education has more policy relevance for local pollution when compared to environmental hazards beyond national boundaries.

Figure 5. Marginal Effects of the *Shadow Economy* on CO₂ Emissions per capita (using S.3.9 in Table 3)



Note: The middle solid line shows the marginal impact of a 1% increase in the size of the shadow economy on CO₂ emission per capita at different levels of corruption. The dashed lines are 90% confidence intervals (CIs).

5. Robustness Checks

Europe and North America (EU & NA) and the Rest of the World

As a robustness check for our analysis, we split the sample between Europe and North America (EU&NA) and the rest of the world.¹⁹ The shadow economy in European and North American countries may be mostly due to tax evasion, whereas firms in low-income countries try to evade (environmental) regulations. Most shadow economy activities in EU&NA are concentrated in the service sector, such as cleaning and personal services. Thus, the destructive effect of the shadow economy on local pollution may not be comparable to its effect in developing countries. Hence, we may not be able to find a noticeable link between corruption and the shadow economy in EU&NA.

Table 4 shows that the increasing effect of the shadow economy on local pollution (SO₂) and interaction term with corruption are statistically significant only for the non-EU&NA countries. When we use CO₂ emission per capita as a pollution indicator, the effect of the shadow economy is positive (increasing) and statistically significant in both cases (including and excluding EU&NA countries).

Measurement Error

Measurements of corruption and the shadow economy may contain some degree of error. Most previous studies measure corruption using instruments, such as ethnic fractionalization, legal origins and absolute latitude in cross-country frameworks. However, the main problem with these instruments is that they are constant over time for each country and therefore cannot be used in a panel data context. As it is difficult to find time-varying instruments for variables such as corruption and the shadow economy, Verbeek (2004, p.345) suggests an alternative route: “*in many cases panel data will provide ‘internal’ instruments for regressors that are subject to measurement error. That is, transformations of the original variables can often be argued to be uncorrelated with the model’s error term and correlated with the explanatory variables themselves and no external instruments are needed*”. In line with this proposal, we use 2 to 3 lags of corruption, the shadow economy and their interaction as instruments. Then, we employ the Durbin-Wu-Hausman specification test to discriminate between the two approaches (IV and OLS). We cannot reject the null hypothesis of no difference in OLS and IV estimates and thus, we infer that it is safe to use OLS.²⁰

¹⁹ We follow the classification of the World Bank.

²⁰ The tables with the regression results are omitted here but are available upon request from the authors.

Table 4. Shadow Economy and Pollution in Different Regions

Panel with fixed country and time effects (OLS)

Dependent variable	CO ₂ per capita		SO ₂ per capita	
	EU&NA	Non-EU&NA	EU&NA	Non-EU&NA
<i>shadow</i>	2.03*** (2.72)	1.50*** (4.20)	3.90 (1.58)	1.91*** (2.55)
<i>trade openness</i>	-0.21 (-1.24)	0.08* (1.75)	0.22 (0.30)	-0.0006 (-0.005)
<i>population density</i>	-0.64 (-0.77)	-0.14 (-0.51)	7.84** (2.21)	-0.05 (-0.10)
<i>urbanization</i>	-0.57 (-0.48)	1.49*** (3.43)	-2.11 (-0.69)	2.83*** (2.75)
<i>pop1564</i>	1.06 (1.00)	1.59** (2.37)	-6.70* (-1.72)	3.11* (1.69)
<i>polity</i>	0.04 (0.16)	-0.20 (-1.39)	2.54*** (2.64)	-0.24 (-1.05)
<i>second_enrol</i>	-0.0002 (-0.28)	0.001 (0.98)	-0.002** (-2.29)	-0.008** (-2.16)
<i>corruption</i>	-0.06 (-0.88)	-0.03 (-0.47)	0.16 (0.76)	-0.23 (-1.33)
<i>shadow*corruption</i>	0.01 (0.70)	0.01 (0.68)	-0.04 (-0.60)	0.08* (1.73)
<i>gdp p.c.</i>	-8.64E-10 (-0.82)	1.65E-05* (1.61)	-1.86E-05 (-0.92)	7.52E-10 (0.28)
<i>gdp p.c.²</i>	2.69E-10** (2.00)	-4.17E-10** (-1.92)	2.22E-10 (1.22)	-2.17E-10 (-0.44)
<i>manufacturing</i>	0.02*** (2.59)	0.009*** (3.27)	0.06*** (3.50)	0.01** (1.96)
Adj. R ²	0.97	0.99	0.97	0.97
Observations	151	447	176	449
Number of countries	27	91	27	80

Note: White robust *t*-statistics are in parentheses.***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Constant term is included (not reported). EU&NA stands for Europe and North America.

Alternative Corruption Indicator

To further test the robustness of our results, we employ the *Corruption Perception Index (CPI)* of Transparency International (TI) as an alternative corruption index that is commonly used in the literature. CPI draws on different assessments and business opinion surveys carried out by independent and reputable institutions to capture information about the administrative and political aspects of corruption. Broadly speaking, the surveys include questions relating to bribery of public officials, kickbacks in public procurement, embezzlement of public funds and questions that probe the strength and effectiveness of public sector anti-corruption efforts. For a country or territory to be included in the index, a

minimum of three of the sources that TI uses must assess that country. For example, the CPI from the year 2005 draws on 16 different polls and surveys from 10 independent institutions.²¹ Some sources of the CPI Index, such as CU (State Capacity Survey by Columbia University), EIU (Economist Intelligence Unit), FH (Freedom House), MIG (Merchant International Group) and WMRC (World Markets Research Centre), mainly gather the perceptions of non-residents from developed countries and draw on their expert opinions about corruption in foreign countries. Other sources, such as II (Information International), are based on the expert opinions of non-residents who are predominantly from less-developed countries. The advantage of using non-residents' opinions is that they are not vulnerable to a home country bias (Lambsdorff, 2007). Other sources include respondents who are nationals of the studied countries, such as IMD (Institute for Management Development), PERC (Political and Economic Risk Consultancy) and WEF (World Economic Forum).

Lambsdorff (2007) shows that there is a significant correlation between the perception (CPI) and the actual experience of corruption. He shows that CPI correlates well with experienced-based data sources, such as the International Crime Victim Survey. The ICVS respondents' personal experience of corruption shows a correlation of over 0.80 with the CPI index of corruption. There is also a high correlation between major corruption indicators, such as PRS, CPI and World Bank (WGI). In our sample, the correlations between CPI, PRS and WGI are 0.85, 0.96 and 0.85, respectively. These findings show that all of these indicators measure the same concept of corruption in public administration.

Table 5 shows the results of the CPI approach. The direct effect of the shadow economy on local (SO₂) and global (CO₂) emission is positive and statistically significant and the amplifying effect of higher corruption is only observed for local air pollution. Hence, the main findings are robust to changes in the corruption measure.

²¹ For further details, see http://www.icgg.org/downloads/CPI_Methodology.pdf.

Table 5. Alternative Corruption Index (CPI)

Panel with fixed country and time effects (OLS)

Dependent variable	SO ₂ per capita		CO ₂ per capita	
Independent variables				
<i>shadow</i>	1.25*** (6.53)	0.84** (2.19)	1.20*** (4.56)	1.03*** (3.19)
<i>trade openness</i>	0.10 (1.26)	0.03 (0.30)	0.04 (0.82)	0.11 (1.54)
<i>population density</i>	-1.16*** (-4.04)	-1.05*** (-2.75)	-0.76*** (-2.84)	-0.34 (-1.06)
<i>urbanization</i>	3.24*** (3.66)	3.07*** (4.09)	1.49** (2.52)	1.19** (1.98)
<i>pop1564</i>	2.89* (1.77)	2.24 (1.01)	0.48 (0.60)	0.15 (0.17)
<i>polity</i>	-0.52*** (-4.98)	-0.60*** (-3.83)	-0.46*** (-2.57)	-0.48*** (-2.60)
<i>second_enrol</i>	-0.002** (-2.29)	-0.003** (-2.11)	-3.43E-05 (-0.05)	-9.70E-05 (-0.15)
<i>corruption</i>	-2.15 (-1.64)	-1.99 (-1.53)	0.97 (0.98)	1.53 (1.48)
<i>shadow*corruption</i>	0.83** (2.12)	0.76** (1.91)	-0.24 (-0.85)	-0.40 (-1.37)
<i>gdp p.c.</i>		0.49 (1.14)		0.14 (0.81)
<i>gdp p.c.²</i>		-0.02 (-0.99)		-0.002 (-0.26)
<i>manufacturing</i>		0.01* (1.82)		0.002 (0.66)
Adj. R2	0.98	0.98	0.99	0.99
Observations	507	485	442	424
Number of countries	108	105	116	111

Note: White robust *t*-statistics are in parentheses.***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively. Constant term is included (not reported).

6. Conclusion

Environmental damage has become a major obstacle to the improvement of living conditions in many developing countries. A large, informal sector may contribute significantly to environmental damage because it is, by definition, unregulated and involves activities that are particularly destructive to the environment. This paper studies the mechanism through which the shadow economy feeds environmental degradation. Our main idea is that corruption reinforces the damaging effects of the shadow economy. In our theoretical model, we show that the shadow economy increases local and global air pollution; however, this effect can be moderated by better control of corruption. To test this hypothesis, we use a reduced form

econometric model and panel data covering the period from 1999-2005 for more than 100 countries. We show that our theoretical prediction is supported by empirical evidence. In the different regressions, the marginal impact of the shadow economy on local and global air pollution is positive. However, this destructive effect can be significantly reduced by lowering the levels of corruption. For example, a reduction in the corruption score from 6 (most corrupt) in Zimbabwe (2005) to a score of 3 (as in neighboring Zambia) would reduce the destructive effects of a large shadow economy (which is approximately 50% of the GDP) and lower local air pollution by 17 percentage points. These findings imply that policy makers may have to address the effects of corruption and/or the main drivers of the shadow economy before increasing environmental standards and regulations.

References

- Alesina, A., Weder, B., 2002. Do Corrupt Governments Receive Less Foreign Aid? *American Economic Review* 92, 155-194.
- Baksi, S., Bose, P., 2010. *Environmental Regulation in the Presence of an Informal Sector*. Working Paper Number: 2010-03, Department of Economics, The University of Winnipeg.
- Bhattacharyya, S., Hodler, R., 2010. Natural Resources, Democracy and Corruption. *European Economic Review* 54, 608-621.
- Biller, D., 1994. *Informal Gold Mining and Mercury Pollution in Brazil*. Policy Research Working Paper 1304. The World Bank, Washington, D.C.
- Bimonte, S., 2002. Information Access, Income Distribution, and the Environmental Kuznets Curve. *Ecological Economics* 41, 145–156.
- Blackman, A., 2000. Informal Sector Pollution Control: What Policy Options Do We Have? *World Development* 28, 2067-2082.
- Blackman, A., Bannister, G., 1998. 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, 1-21.
- Bollen, K.A. 1989. *Structural Equations with Latent Variables*, Wiley, New York.
- Botero, J., Djankov, S., Porta, R., Lopez-De-Silanes, F.C., 2004. The Regulation of Labor. *Quarterly Journal of Economics* 119, 1339-1382.
- Buehn, A., Farzanegan, M.R., 2012. Smuggling around the World: Evidence from a Structural Equation Model, *Applied Economics* 44, 3047-3064.
- Chang, C., Lee, A., Lee, C., 2009. Determinants of capital structure choice: A structural equation modeling approach. *The Quarterly Review of Economics and Finance* 49, 197-213.
- Chaudhuri, S., Mukhopadhyay, U., 2006. Pollution and Informal Sector: A Theoretical Analysis. *Journal of Economic Integration* 21, 363 – 378.
- Choi, J. P, Thum, M., 2004. The Economics of Repeated Extortion. *Rand Journal of Economics* 35, 203-223.
- Choi, J. P, Thum, M., 2005. Corruption and the Shadow Economy, *International Economic Review* 46, 817-836.
- Cole, M. A., 2004. Trade, the Pollution Haven Hypothesis and the Environmental Kuznets Curve: Examining the Linkages. *Ecological Economics* 48, 71–81.
- Cole, M.A., 2007. Corruption, Income and the Environment: An empirical analysis. *Ecological Economics* 62, 637-647
- Cole, M.A., Rayner, A.J., Bates, J.M., 1997. The Environmental Kuznets Curve: An Empirical Analysis. *Environment and Development Economics* 2, 401-416.
- Copeland, B., Taylor, M.S., 2003. *Trade and the Environment: Theory and Evidence*, Princeton University Press: Princeton.
- Dinda, S., Coondoo, D., Pal, M., 2000. Air Quality and Economic Growth: An Empirical Study. *Ecological Economics* 34, 409–423.

- Dondeyne, S., Ndunguru, E., Rafael, P., Bannerman, J., 2009. Artisanal Mining in Central Mozambique: Policy and Environmental Issues of Concern. *Resources Policy* 34, 45-50.
- Dougherty, C., 2011. *Introduction to Econometrics* (4th Ed.). New York: Oxford University Press.
- Farzanegan, M.R., 2009. Illegal Trade in the Iranian Economy: Evidence from Structural Equation Model. *European Journal of Political Economy* 25, 489-507.
- Farzin, Y.H., Bond, C.A., 2006. Democracy and Environmental Quality. *Journal of Development Economics* 81, 213-235.
- Feige, E. L., 1994. The Underground Economy and the Currency Enigma. *Public Finance/Finances Publiques* 49 (Supplement), 119-136.
- Fowlie, M. L., 2009. Incomplete Environmental Regulation, Imperfect Competition, and Emissions Leakage. *American Economic Journal: Economic Policy* 1, 72-112.
- Fredriksson, P.G., Svensson, J., 2003. Political Instability, Corruption and Policy Formation: the Case of Environmental Policy. *Journal of Public Economics* 87, 1383-1405.
- Friedl, B., Getzner, M., 2003. Determinants of CO2 Emissions in a Small Open Economy. *Ecological Economics* 45, 133– 148.
- Grossman, G.M., Krueger, A.B., 1994. Economic Growth and the Environment. *The Quarterly Journal of Economics* 110, 353-377
- Hausman, J.A., 1978. Specification Tests in Econometrics, *Econometrica* 46, 1251–1271.
- Herwartz, H., 2010. A Note on Model Selection in (Time Series) Regression Models - General-to-specific or Specific-to-general? *Applied Economics Letters* 17, 1157–1160.
- ILO, 2010. *Key Indicators of the Labour Market (KILM)*, Sixth Edition. International Labour Organization, Geneva.
- Knack, S., Keefer, P., 1995. Institutions and Economic Performance: Cross-country Tests Using Alternative Institutional Measures. *Economics and Politics* 7, 207-227.
- Lahiri-Dutt, K., 2004. Informality in Mineral Resource Management in Asia: Raising Questions Relating to Community Economies and Sustainable Development. *Natural Resources Forum* 28, 123–132.
- Lambdorff, G., 2007. *The Institutional Economics of Corruption and Reform: Theory, Evidence, and Policy*. Cambridge MA: Cambridge University Press.
- Lopez, R., Mitra, S., 2000. Corruption, Pollution, and the Kuznets Environment Curve. *Journal of Environmental Economics and Management* 40, 137-150
- Marshall, M., Gurr, T., Jagers, K., 2009. *Polity IV Project: Political Regime Characteristic and Transitions, 1800-2009*. University of Maryland.
- Mauro, P., 1995. Corruption and Growth. *Quarterly Journal of Economics* 110, 681–712.
- Mo, P. H., 2001. Corruption and Economic Growth. *Journal of Comparative Economics* 29, 66–79.

- Panayotou, T., 1997. Demystifying the Environmental Kuznets Curve: Turning a Black Box into a Policy Tool. *Environment and Development Economics* 2, 465–484.
- Pellegrini, L., Gerlagh, R., 2006. Corruption, Democracy and Environmental Policy: An Empirical Contribution to the Debate. *Journal of Environment and Development* 15, 332-354.
- Rivera-Batiz, F.L., 2002. Democracy, Governance, and Economic Growth: Theory and Evidence. *Review of Development Economics* 6, 225–247.
- Schneider, F., 1994. Measuring the Size and Development of the Shadow Economy. Can the Causes be Found and the Obstacles Be Overcome? In: Brandstaetter, H., and Güth, W. (eds.): *Essays on Economic Psychology*, Springer, Berlin, Heidelberg, 193-212.
- Schneider, F., Buehn, A., Montenegro, C.E., 2010. *Shadow Economies All over the World: New Estimates for 162 Countries from 1999 to 2007*. World Bank Policy Research Working Paper No.5356. Washington D.C.
- Schneider, F., Enste, D., 2000. Shadow Economies: Size, Causes, and Consequences. *Journal of Economic Literature* 38, 77–114.
- Scruggs, L.A., 1998. Political and Economic Inequality and the Environment. *Ecological Economics* 26, 259–275.
- Selden, T.M., Song, D., 1994. Environmental Quality and Development: Is There a Kuznets Curve for Air Pollution Emissions? *Journal of Environmental Economics and Management* 27, 147-162.
- Shleifer, A., Vishny, R. W., 1993. Corruption. *Quarterly Journal of Economics* 108, 599-617.
- Smith, S.J., van Aardenne, J., Klimont, Z., Andres, R., Volke, A., Delgado Arias, S., 2011. Anthropogenic Sulfur Dioxide Emissions: 1850–2005. *Atmospheric Chemistry and Physics (ACP)* 11, 1101-1116.
- Stern, D., 2004. The Rise and Fall of the Environmental Kuznets Curve. *World Development* 32, 1419-1439.
- Tanzi, V., Davoodi, H. 2001. Corruption, Growth, and Public Finances. In: Jain, A. K. (Ed.): *Political Economy of Corruption*, Routledge, London, 89–110.
- Torras, M., Boyce, J.K., 1998. Income, Inequality, and Pollution: A Reassessment of the Environmental Kuznets Curve. *Ecological Economics* 25, 147–160.
- Veiga, M.M., Meech, J.A., Oñates, N., 1994. Mercury Pollution from Deforestation. *Nature* 368, 816-817.
- Verbeek, M., 2004. *A Guide to Modern Econometrics*. (2nd Ed.). John Wiley & Sons, West Sussex.
- Welsch, H., 2004. Corruption, Growth, and the Environment: A Cross-country Analysis. *Environment and Development Economics* 9, 663-693.
- World Bank, 2011. *World Development Indicators* World Bank, Washington D.C.

Appendix A

Data Sources and Definitions

<i>Variable</i>	<i>Definition</i>	<i>Source</i>
<i>CO₂ per capita</i>	Logarithm of CO ₂ emission (metric tons) per capita. Carbon dioxide emissions are those released by the burning of fossil fuels and the manufacture of cement. They include carbon dioxide produced during the consumption of solid, liquid and gas fuels and gas flaring.	World Bank (2011)
<i>SO₂ per capita</i>	Logarithm of SO ₂ emission per capita. Sulfur emissions from combustion and metal smelting can, in principle, be estimated using a bottom-up mass balance approach where emissions are equal to the sulfur content of the fuel (or ore) minus the amount of sulfur removed or retained in bottom ash or in products. Emissions were estimated annually by country for the following sectors: coal combustion, petroleum combustion, biomass combustion, shipping bunker fuels, metal smelting, natural gas processing and combustion, petroleum processing, pulp and paper processing, other industrial processes and agricultural waste burning (AWB). We divided the absolute amount of SO ₂ (Gg) by the population to calculate the per capita SO ₂ .	SO ₂ data from Smith et al. (2011) and total population from the World Bank (2011).
<i>shadow</i>	Logarithm of the shadow economy (as % of GDP). Size of the shadow economy as a percent of the GDP calculated with MIMIC and currency demand estimation techniques. Causes: Share of direct taxation (in percent of GDP), share of indirect taxation and custom duties (in percent of GDP), regulatory quality (measures of the incidence of market-unfriendly policies, such as price controls or inadequate bank supervision as well as the perceptions of the burdens imposed by excessive regulation in areas, such as foreign trade and business development), unemployment quota (% of total labor force), GDP p.c. (GDP per capita based on purchasing power parity (PPP; constant 2005 international \$), business freedom (measures the time and efforts of business activity and ranges from 0 to 100, where 0 = least business freedom and 100 = maximum business freedom), fiscal freedom (measures the fiscal burden in an economy, i.e., the top tax rates on individual and corporate income and ranges from 0 to 100, where 0 = least fiscal freedom and 100 = maximum fiscal freedom), size of government (general government	Schneider et al. (2010)

final consumption expenditure (% of GDP)) and government effectiveness (captures perceptions of the quality of public services, the quality of civil service and the degree of its independence from political pressures, the quality of policy formulation and implementation and the credibility of the government's commitment to such policies).

Indicators: labor force participation rate, growth rate of GDP per capita, change of currency (growth rate of change of currency per capita).

<i>energy efficiency</i>	Logarithm of GDP per unit of energy use (constant 2005 PPP \$ per kg of oil equivalent).	World Bank (2011)
<i>trade openness</i>	Logarithm of trade openness. Trade is the sum of exports and imports of goods and services measured as a share of the GDP.	World Bank (2011)
<i>urbanization</i>	Logarithm of urban population (% of total).	World Bank (2011)
<i>population density</i>	Logarithm of population density (people per sq. km).	World Bank (2011)
<i>pop1564</i>	The logarithm of the population aged 15 to 64 is the percentage of the total population that is in the age range 15 to 64.	World Bank (2011)
<i>second_enrol</i>	School enrollment, secondary (% gross).	World Bank (2011)
<i>polity</i>	Polity2 index, -10: fully non-democratic, 10: fully democratic. Rescaled from 0 (least democratic) to 1 (most democratic). Logarithm of polity (rescaled plus 1).	Marshall et al. (2009)
<i>corruption</i>	Corruption index of ICRG: actual or potential corruption in the form of excessive patronage, nepotism, job reservations, 'favor-for-favor', secret party funding and suspiciously close ties between politics and business. Rescaled from 0 (free of corruption) to 6 (highest level of corruption). An alternative indicator is <i>Corruption Perception Index</i> by Transparency International. The index ranges from 0 (most corrupt) to 10 (least corrupt). Recoded CPI index is used; higher scores indicate higher corruption.	ICRG, The PRS group: http://www.prsgroup.com/ICRG_Methodology.aspx and CPI from http://www.icgg.org/
<i>gdp p.c.</i>	Logarithm of GDP per capita (current US\$). GDP per capita is the GDP divided by the mid-year population. GDP is the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without	World Bank (2011)

making deductions for the depreciation of fabricated assets or for the depletion and degradation of natural resources. Data are in current U.S. dollars.

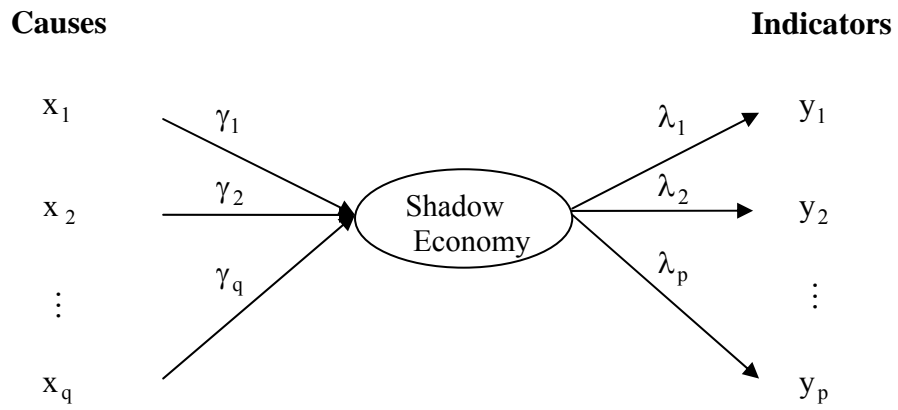
manufacturing Manufacturing, value added (% of GDP). World Bank
Manufacturing refers to industries belonging to ISIC (2011)
divisions 15-37. Value added is the net output of a
sector after adding up all outputs and subtracting
intermediate inputs. It is calculated without making
deductions for the depreciation of fabricated assets or
the depletion and degradation of natural resources.
The origin of value added is determined by the
International Standard Industrial Classification
(ISIC), revision 3.

Appendix B: A Brief Review of Shadow Economy Estimations

The MIMIC (multiple indicators multiple causes) models are based on Structural Equation Modeling. As the shadow economy is not directly observable, it is treated as a latent variable in this framework. Essentially, the latent variable (shadow economy) can be measured indirectly by estimating the link between the observable causes and measurable consequences of the shadow economy. The MIMIC model has two parts: the structural model and the measurement model. The structural model defines the link between the causal variables and the latent variable (shadow economy). The measurement model shows the relationship between the latent variable and its indicators. Figure B1 illustrates the structure of the MIMIC model.

In the estimations by Schneider et al. (2010), the main causes of the shadow economy are size of government, share of direct taxation, fiscal freedom, business freedom, unemployment rate, GDP per capita and government effectiveness index. The indicators of the shadow economy include the growth rate of GDP per capita, the labor force participation rate, the growth rate of the labor force and the domestic currency in circulation (i.e., cash outside the banking system). In the first step, Schneider et al. (2010) calculate an index of the shadow economy by multiplying the coefficients of the statistically significant coefficients in the structural part of model with the respective time series of causal variables. In the second step, they convert the ordinal index of the shadow economy into a cardinal index (relative size of the shadow economy in GDP) using a calibration procedure.

Figure B1. Structure of the MIMIC Model



Note: The coefficients of the structural model and the measurement model are denoted by γ and λ , respectively.