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Shadow Economies in OECD Countries:

DGE vs. MIMIC Approaches

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and

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Abstract: In this paper we compare the level and driving forces of shadow economies in 38 OECD countries using two different methodologies. One of these is the multiple-indicators-multiple-causes (MIMIC) approach based on an estimation of a structural equation model. The other one is based on a two-sector dynamic general equilibrium (DGE) model developed by Elgin and Oztunali. The average driving forces of the shadow economy of the 38 OECD countries obtained using the MIMIC model show that personal income tax (13.8 %), indirect taxes (14.1 %), tax morale (14.5 %), unemployment (14.7 %), self-employment (14.5 %), growth of GDP (14. 3 %) and business freedom index (14. 2 %) contribute more or less evenly to shadow economies. However, according to the estimates constructed using the DGE model growth of GDP per-capita has by far the largest effect (24. 7%) followed by indirect taxes (18. 5 %), unemployment (18.3 %), tax morale (17.1 %), personal income tax (11.2 %), self-employment (5.8 %), and business freedom (4.3 %).

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1. INTRODUCTION

Shadow economy, sometimes also titled black, hidden, informal, parallel, second or underground economy (or sector) is generally defined as a set of economic activities that takes place outside the framework of bureaucratic public and private sector establishments. It is mainly regarded as a sector, which produces legal goods, but does not comply with government regulations. As the shadow economy severely undermines a government's fiscal stance, reducing the shadow economy size and fighting tax evasion are among the roadmaps of any government. This is one of the main reasons of why there is an increasing attention on the economic analysis of the shadow economy in recent years. However, one particular setback, which, despite the development of various methods, still persists in the literature, is the lack of consensus on the measurement of the shadow economy, inhibiting construction of significantly large datasets that would make informality subject to robust (applied) policy analysis.

Even though, there are various methodologies suggested for the measurement of the shadow economy size, this issue mostly arises due to the fact that the size of the shadow economy, by definition, is hard to measure. Most of the suggested methodologies with two exceptions are usually used for a particular country or even a region and could not be generalized to cross-country panel frameworks. One such exception is the dataset presented by Buehn and Schneider (2012a), which reports shadow economy size (as % of GDP) for 162 countries in an annual basis for the 9 years between 1999 and 2007. In this study, the authors rely on the MIMIC (Multiple Indicators and Multiple Causes) approach to estimate the size of the shadow economy and this approach has been extended in more recent papers. (See Buehn and Schneider, 2012b, 2013 and Schneider, 2013) On the other hand, another recently developed approach by Elgin and Oztunali (2012) is based on the calibration-simulation of a two-sector (formal and shadow) dynamic general equilibrium (DGE) model. In their paper the authors use the model to construct an annual unbalanced panel dataset of shadow economy size (as % of GDP) for 161 countries in an annual basis for the 61 years between 1950 and 2010.

In this paper and for the first time we aim to make two contributions: First, we critically compare the two (relatively large) panel datasets on shadow economy size. Second and more importantly we analyze and compare the relative impacts of the causal variables on the size and development of the shadow economy in these two datasets. Our analysis shows that even though the two datasets are similar in levels and both illustrate a declining trend of shadow economy size over the period of analysis, they indicate certain differences with respect to the effects of causal variables on shadow economies. Particularly, the estimates obtained using the MIMIC model imply that the all the seven examined driving forces of shadow economies have similar effects in magnitude. Between 1999 and 2010 unemployment and self-employment on average have the largest impacts (both 14.6 %), follows by tax morale (14. 5%), growth of GDP per-capita (14.3 %), business freedom (14. 2 %) indirect taxes (14. 1 %) and personal income tax (13. 8 %). However, according to the estimates constructed using the DGE model growth of GDP per-capita has by far the largest effect (24. 8%) followed by indirect taxes (18. 5 %), unemployment (18.2 %), tax morale (17.1 %), personal income tax (11.2 %), self-employment (5.8 %), and business freedom index (4.3 %). These striking differences in the estimated effects of the causal variables indicate that the policy recommendations of both approaches are also different.

The reminder of the paper is organized as follows: Section 2 reviews the two main approaches (MIMIC and the DGE) to estimate shadow economy size. Next, in section 3 we present shadow economy size estimations using these two approaches and make a comparison between them. Then, in section 4 we analyze the relative impacts of the causal variables on the size and development of the shadow economy. Finally, in section 5 we provide concluding remarks and a discussion.

2. MEASURING SHADOW ECONOMIES

There are numerous approaches to measure the size and development of a shadow economy and they will not be evaluated here[1]. Among these we will concentrate on the MIMIC and DGE approaches.

2.1 MIMIC Approach

The MIMIC approach generally builds upon the works of Weck (1983) and of Frey and Weck-Hannemann (1983) and is essentially based on the use of a specific structural equation model. It is based on the statistical theory of unobserved variables, which considers multiple causes and indicators of the phenomenon to be measured, i.e. it explicitly considers multiple causes leading to the existence and growth of the shadow economy, as well as the multiple

[1] See Schneider and Enste (2000), Feld and Schneider (2010), Schneider (2011), and Schneider and Williams (2013) for evalulations of different approaches to measure shadow economy size.

effects of the shadow economy over time.[2] In particular, we use a Multiple Indicators Multiple Causes (MIMIC) model – a particular type of a structural equations model (SEM) – to analyze and estimate the shadow economies of 162 countries around the world.[3]

The main idea behind SEM is to examine the relationships among unobserved variables with respect to the relationships among a set of observed variables by using the covariance information of the latter. In particular, SEM compare a sample covariance matrix, i.e. the covariance matrix of the observed variables, with the parametric structure imposed on it by a hypothesized model.[4] The relationships among the observed variables are described in terms of their covariances and it is assumed that they are generated by (a usually smaller number of) unobserved variables. In MIMIC models, the shadow economy is the unobserved variable and is analyzed with respect to its relationship to the observed variables using the covariance matrix of the latter. For this purpose, the unobserved variable is first linked to the observed indicator variables in a factor analytical model, also called a measurement model. Second, the relationships between the unobserved variable and the observed explanatory (causal) variables are specified through a structural model. Thus, a MIMIC model is the simultaneous specification of a factor model and a structural model. In this sense, the MIMIC model tests the consistency of a “structural” theory through data and is thus a rather confirmatory than exploratory technique. In fact, in a confirmatory factor analysis a model is constructed in advance; whether an unobserved (latent) variable or factor influences an observed variable is specified by the researcher, and parameter constraints are often imposed. Thus, an economic theory is tested by examining the consistency of actual data with the hypothesized relationships between observed (measured) variables and the unobserved variable.[5] Such a confirmatory fac-

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[2] This part closely follows Schneider, Buehn and Montenegro (2010), pp 9-13.

[3] The latest papers dealing extensively with the MIMIC approach, its development and its weaknesses are from Giles (1999a, 1999b, 1999c), Giles, Tedds and Werkneh (2002), Dell’Anno (2003), and the excellent study by Giles and Tedds (2002), as well as Bajada and Schneider (2005), Breusch (2005a, 2005b), Schneider (2005, 2007), Pickhardt and Sardà Pons (2006), Chatterjee, Chaudhury and Schneider (2006), Buehn, Karmann, and Schneider (2009), and for a detailed discussion of the strengths and weaknesses see Dell’Anno and Schneider (2009).

[4] Estimation of a SEM with latent variables can be done by means of a computer program for the analysis of covariance structures, such as LISREL (Linear Structural Relations). A useful overview of the LISREL software package in an economics journal is Cziraky (2004). General overviews about the SEM approach are given in e.g. Hayduk (1987), Bollen (1989), Hoyle (1995), Maruyama (1997), Byrne (1998), Muthen (2002), Cziraky (2005).

[5] On the contrary, in an exploratory factor analysis a model is not specified in advance, i.e. beyond the specification of the number of latent variables (factors) and observed variables the researcher does not specify any structure of the model. This means assuming that all factors are correlated, all observed variables are directly influenced by all factors, and measurement errors are all uncorrelated with each other. In practice however, the distinction between a confirmatory and an exploratory factor analysis is less strong. Facing poorly fitting models, researchers using SEM techniques or a confirmatory factor analysis often modify their models in an exploratory

tor analysis has two goals: (i) estimating the parameters (coefficients, variances, etc.), and (ii) assessing the fit of the model. Applying this to the shadow economy research, these two goals mean: (a) measuring the relationships of a set of observed causes and indicators to the shadow economy (latent variable), and (b) testing if the researcher's theory or the derived hypotheses, as a whole, fit the data used.

Formally, the MIMIC model consists of two parts: the structural equation model and the measurement model. The structural equation model is given by:

$$\eta = \boldsymbol{\gamma}'\mathbf{x} + \varsigma \ , (1)$$

where $\mathbf{x}' = (x_1, x_2, \ldots, x_q)$ is a $(1 \times q)$ vector and each x_i , $i = 1, \ldots, q$ is a potential cause of the latent variable η and $\boldsymbol{\gamma}' = (\gamma_1, \gamma_2, \ldots, \gamma_q)$ is a $(1 \times q)$ vector of coefficients describing the relationships between the latent variable and its causes. Thus, the latent variable η is determined by a set of exogenous causes. Since these causes only partially explain the latent variable η, the error term ς represents the unexplained component. The variance of ς is denoted by ψ. $\boldsymbol{\Phi}$ is the $(q \times q)$ covariance matrix of the causes $\mathbf{x}$. The measurement model represents the link between the latent variable and its indicators, i.e. the latent variable determines its indicators. The measurement model is specified by:

$$\mathbf{y} = \boldsymbol{\lambda}\eta + \varepsilon \ , (2)$$

where $\mathbf{y}' = (y_1, y_2, \ldots, y_p)$ is a $(1 \times p)$ vector of several indicator variables. $\boldsymbol{\lambda}$ is the vector of regression coefficients, and $\boldsymbol{\varepsilon}'$ is a $(1 \times p)$ vector of white noise disturbances. Their $(p \times p)$ covariance matrix is given by $\boldsymbol{\Theta}_\varepsilon$. Figure 1 shows the structure of the MIMIC model using a path diagram.

way in order to improve the fit. Thus, most applications fall between the two extreme cases of confirmatory (non-specified model structure) and exploratory (ex-ante specified model) factor analysis.

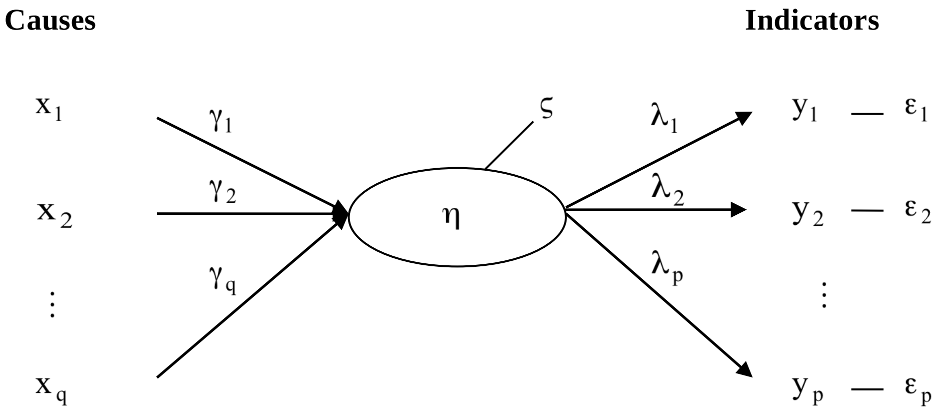


Figure 1. General Structure of a MIMIC Model

Using equation (1) in equation (2) yields a reduced form multivariate regression model where the endogenous variables y_j , $j = 1,\ldots, p$ are the latent variable η 's indicators and the exogenous variables x_i , $i = 1,\ldots,q$ its causes. This model is given by:

$$\mathbf{y} = \mathbf{\Pi x} + \mathbf{z} \ , \ (3)$$

where $\mathbf{\Pi} = \boldsymbol{\lambda\gamma}'$ is a matrix with rank equal to 1 and $z = \lambda\varsigma + \varepsilon$. The error term $\mathbf{z}$ in equation (3) is a $(p \times 1)$ vector of linear combinations of the white noise error terms ς and $\boldsymbol{\varepsilon}$ from the structural equation and the measurement model, i.e. $\mathbf{z} \sim (\mathbf{0}, \mathbf{\Omega})$. The covariance matrix $\mathbf{\Omega}$ is given by $\mathbf{Cov}(\mathbf{z}) = \mathbf{E}[(\boldsymbol{\lambda}\varsigma + \boldsymbol{\varepsilon})(\boldsymbol{\lambda}\varsigma + \boldsymbol{\varepsilon})'] = \boldsymbol{\lambda\lambda}'\psi + \mathbf{\Theta}_{\varepsilon}$ and is similarly constrained like $\mathbf{\Pi}$. The identification and estimation of the model therefore requires the normalization of one of the elements of the vector $\boldsymbol{\lambda}$ to an *a priori* value (Bollen 1989). From equations (1) and (2) we can derive the MIMIC model's covariance matrix $\mathbf{\Sigma}(\boldsymbol{\theta})$. This matrix describes the relationship between the observed variables in terms of their covariances. Decomposing the matrix yields the structure between the observed variables and the latent variable. This covariance matrix is given by:

$$\mathbf{\Sigma}(\boldsymbol{\theta}) = \begin{pmatrix} \boldsymbol{\lambda}(\boldsymbol{\gamma}'\mathbf{\Phi}\boldsymbol{\gamma} + \psi) + \mathbf{\Theta}_{\varepsilon} & \boldsymbol{\lambda\gamma}'\mathbf{\Phi} \\ \mathbf{\Phi}\boldsymbol{\gamma\lambda}' & \mathbf{\Phi} \end{pmatrix}, \ (4)$$

where $\mathbf{\Sigma}(\boldsymbol{\theta})$ is a function of the parameters $\boldsymbol{\lambda}$ and $\boldsymbol{\gamma}$ and of the covariances contained in $\mathbf{\Phi}$, $\mathbf{\Theta}_{\boldsymbol{\varepsilon}}$, and ψ. If the hypothesized model is correct and the parameters are known, the population covariance matrix $\mathbf{\Sigma}$ would be exactly reproduced by estimation of the model, i.e $\mathbf{\Sigma}$ will equal $\mathbf{\Sigma}(\theta)$. In practice, one does however not know either the population variances and covariances, or the parameters but uses the sample covariance matrix of the observed variables, i.e. of $\mathbf{y}$ (vector of indicators) and $\mathbf{x}$ (vector of causes), and sample estimates of the unknown parameters for estimation of the model. The goal of the estimation procedure then is to estimate the parameters and covariances that produce an estimate for $\mathbf{\Sigma}(\boldsymbol{\theta})$, $\hat{\mathbf{\Sigma}} = \mathbf{\Sigma}(\hat{\boldsymbol{\theta}})$ that is as close as possible to the sample covariance matrix of the observed causes and indicators. The function that measures how close a given $\mathbf{\Sigma}^*$ is to the sample covariance matrix $\mathbf{S}$ is called fitting function $\mathrm{F}(\mathbf{S};\mathbf{\Sigma}^*)$. The most widely used fitting function for SEM is the Maximum Likelihood (ML) function:

$$\mathrm{F}_{\mathrm{ML}} = \log\left|\mathbf{\Sigma}(\theta)\right| + tr\left[\mathbf{S}\mathbf{\Sigma}^{-\mathbf{1}}(\theta)\right] - \log\left|\mathbf{S}\right| - (\mathrm{p}+\mathrm{q}) \,, \quad (5)$$

where $\log|\ |$ is the log of the respective matrix's determinant and $(\mathrm{p}+\mathrm{q})$ is the number of observable variables. In general, no closed form or explicit solution for the structural parameters that minimize F_{ML} exists. Hence, the estimates that minimize the fitting function are derived applying iterative numerical procedures (see appendix 4C in Bollen (1989) for details).

In summary, the first step in the MIMIC model estimation is to confirm the hypothesized relationships between the shadow economy (the latent variable) and its causes and indicators. Once the relationships are identified and the parameters estimated, the MIMIC model results are used to calculate the MIMIC index. However, this analysis provides only relative estimates, not absolute, of the size of the shadow economy. Therefore an additional procedure, benchmarking or calibration procedure, is required in order to calculate absolute values of the size of the shadow economy.

The MIMIC approach is generally praised for its formalization of the shadow economy as the outcome of a multitude of causes like taxes, unemployment and institutional quality indices. However, it has been also criticized for being based on the use of certain ad-hoc econometric specifications thereby making it subject to measurement errors. Moreover, another shortcoming of this approach is that it does not rely on any micro-foundations. Breusch (2005a, 2005b) is one of the heavy critics of using the MIMIC approach for this purpose[6].

In this paper, we use the MIMIC estimates of Buehn and Schneider (2013) for 38 countries from 1999 to 2010 in which the authors use personal income tax (as % of GDP), payroll taxes, indirect taxes (both as % of total tax revenue), tax morale (an index obtained from World Values Survey measuring the extent to which cheating on taxes is justified or not), unemployment (% of total labor force), business freedom (an index measuring efficiency of government regulation of business, obtained from the Heritage Foundation), self-employment (% of total employment), rule of law (an index summarizing the quality of contract enforcement, the police, and the courts, as well as the likelihood of crime and violence,), growth of GDP per-capita (in %) education (secondary school enrollment ratio in gross %) and corruption index (measuring the extent to which corruption prevails in a country) among causes, and GDP per-capita (in constant 2005 USD), currency in circulation (as a ratio to M1) and labor force participation rate (% of total working-age population) among indicators of shadow economies.

2.2 DGE Approach

In a recent paper Elgin and Oztunali (2012) use a two-sector dynamic general equilibrium model and present a new approach to estimate the size of the shadow economy. Their micro-founded methodology uses national income statistics and a DGE to back out shadow economy size from the model. Using this model the authors construct an annual unbalanced 161-country panel dataset over the period from 1950 to 2010. This aims to be the largest dataset in the literature, particularly with its time-series dimension. Among many possible advantages regarding its use, the construction of such a dataset would also allow for various policy analyses that require a significantly large time dimension. However, one possible criticism towards this approach can be made regarding its reliance on the use of national income statis-

[6] See also the „reply“ by Dell´Anno and Schneider (2006, 2009).

tics, which limits the number of variables that potentially might affect or be affected from shadow economy size.

To illustrate, how one can construct a shadow economy series for a particular country using this approach, we can assume a simple representative-agent environment consisting of a representative (stand-in) household-firm that obtains utility from consumption and leisure. This agent is assumed to maximize the following discounted (at rate $0 < \beta < 1$) utility:

$$\sum_{t=0}^{\infty} \beta^t U(C_t, L_t)$$

subject to the following two constraints:

$$C_t + K_{t+1} - (1-\delta)K_t = (1-\tau)\theta_{F,t} K_t^{\alpha} N_{F,t}^{\alpha} + \theta_{S,t} N_{S,t}^{\gamma}$$

$$N_{F,t} + N_{S,t} + L_t = T$$

In this setup, the representative household-firm lives infinitely, has initially K_0 units of capital and T>0 units of time endowment in every period. The household has access to two production technologies: It can produce in the formal (official) or informal (shadow) sector. In this specification C_t denotes consumption, L_t denotes leisure. Formal sector exhibits constant returns to scale production, which equals $\theta_{F,t} K_t^{\alpha} N_{Ft}^{1-\alpha}$, where $\theta_{F,t}$ is the total factor productivity (TFP) in the formal sector and N_{Ft} represents time devoted to working in the formal sector. The formal sector production function uses both capital (which depreciates at a rate equal to δ) and labor as inputs. Notice that income of this household-firm from the formal sector is taxed at the rate τ. The informal sector technology, using only labor as input, on the other hand is characterized by $\theta_{S,t} N_{St}^{\gamma}$, where $\theta_{S,t}$ is the TFP parameter and N_{St} represents time spent working in the informal sector. When operating in the informal economy, this agent hides his income generated from this sector, as he does not pay any taxes for informal sector income. In this setup the first constraint is the budget constraint of this representative agent and the second equation denotes the time constraint. Moreover, it is also assumed that government's policy variable $\{\tau\}$ is exogenous and government revenue G_t is spent on unproductive activities, which neither generates utility for household nor improves production technologies.[7] Once we define a competitive equilibrium for this environment and solve it at the steady-state we end up with the following equation defining informal labor at the steady state as a function of various parameters of the economy:

$$N_{S_t} = \left\{ \frac{\gamma \theta_{S_t}}{(1-\tau_t)(1-\alpha)\theta_{F_t}} \left[\frac{(1)/\beta - 1 + \delta}{\alpha(1-\tau_t)\theta_{F_t}} \right]^{\frac{\alpha}{1-\alpha}} \right\}^{\frac{1}{1-\gamma}}$$

To back out the shadow economy size for a specific country and year, Elgin and Oztunali (2012) first, through calibration or assumption, set the values of several parameters of the economy (such as β, δ, γ, and α), next obtain the total factor productivities of both sectors from the model and then us the equation-above to back out informal labor N_{St}. Then it is just a matter of calculation to construct the shadow economy size series (as % of GDP) for 161 countries from 1950 to 2010. (In model's terms this corresponds to $\frac{\theta_{S,t} N_{S,t}^{\gamma}}{\theta_{F,t} K_t^{\alpha} N_{F,t}^{\alpha}}$.) One particular feature of this process is that, through the construction of the series, the authors calibrate one particular parameter of the model to match the shadow economy size in 2007 of the series reported in Buehn and Schneider (2012). The authors then use several series from Penn World Tables (namely consumption, working-age population, employment, GDP per-capita, investment, government spending) to construct the shadow economy dataset. In this paper we use the series constructed by Elgin and Oztunali (2012) for 38 OECD economies from 1999 to 2010.

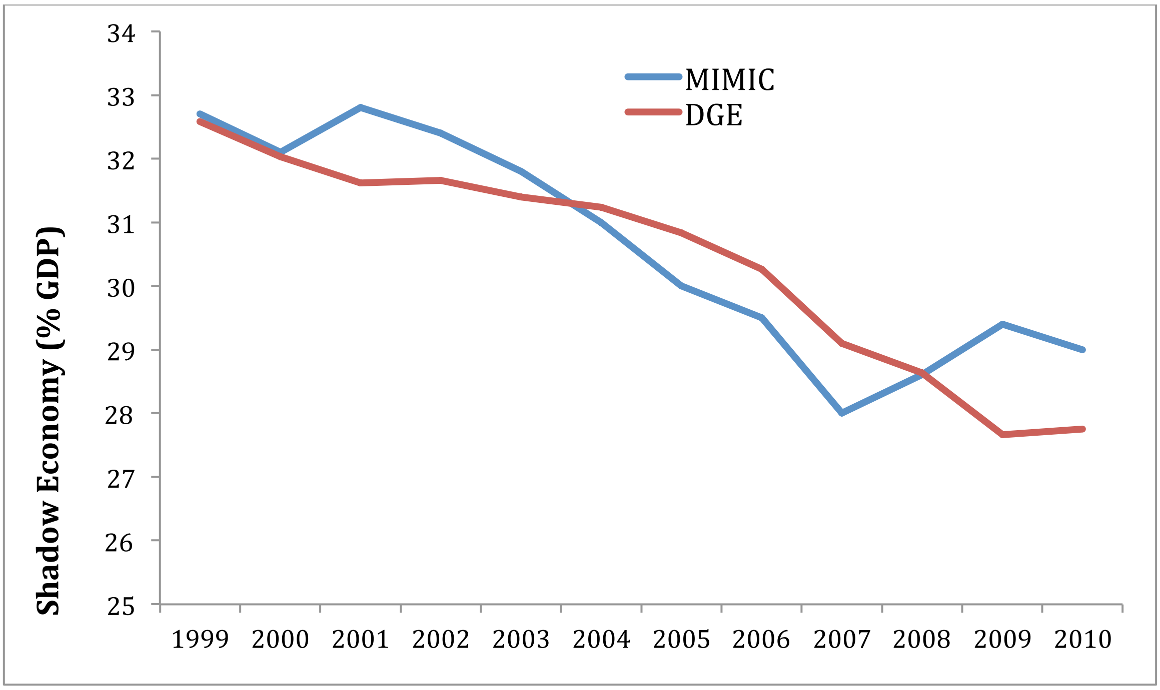
To further illustrate the construction of the DGE dataset, let us chose two structurally different countries within the OECD and explain in more detail how the constructed series look like. For this purpose, we have chosen Austria and Turkey. For the benchmark case reported in Elgin and Oztunali (2012) we chose α, δ and γ to be equal to 0.36, 0.08 and 0.425 respectively.[8] Next, β is calibrated using the Euler equation obtained from the first-order conditions of the maximization problem defined above. The calibrated values for the discount factor are 0.957 and 0.83 for Austria and Turkey, respectively. Once these parameters are set we can then use another equation obtained from the first-order conditions of the model, namely the

[7] Notice that this is a very simple environment and Roca, Morena and Sanchez (2001) and Busato and Chiarini (2004), Ihrig and Moe (2004) amd more recently Elgin and Oztunali (2012) use variations of this setup when modeling informality in a dynamic general equilibrium environment.

[8] Notice that Elgin and Oztunali (2012) conduct several robustness cheks with respect to the different values of these parameters and find that the results are not sensitive to the parameter choice.

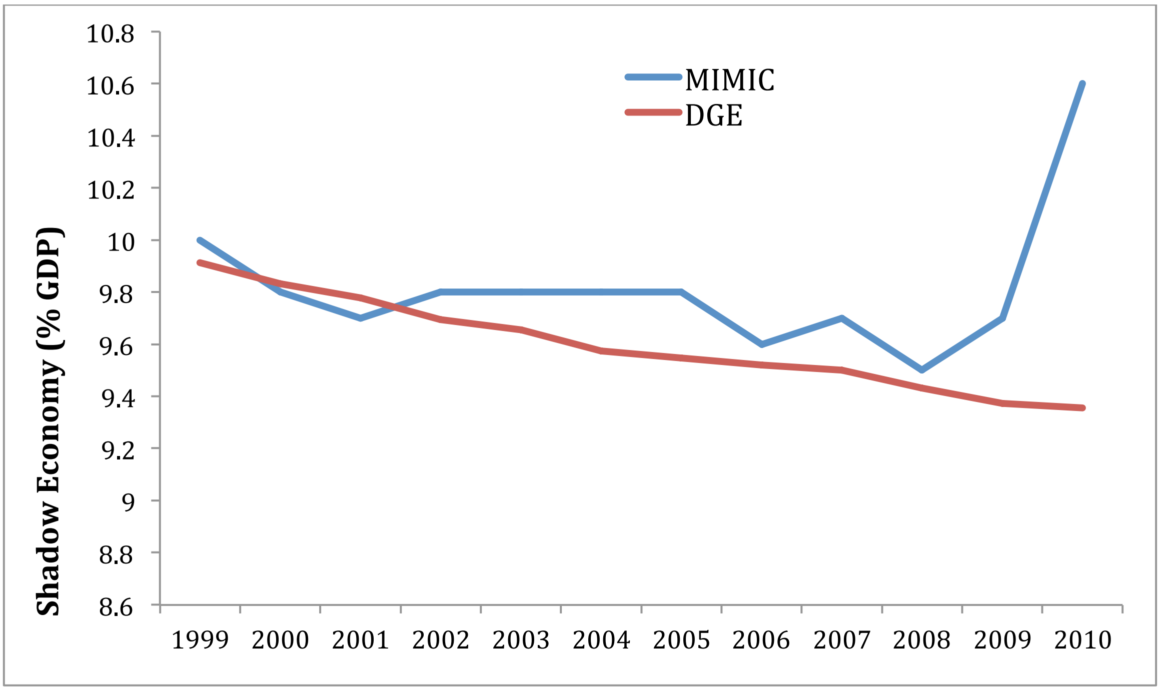
equation relating physical capital to labor in the formal sector. Plugging in the formal employment, capital (constructed using the perpetual inventory method) and taxes from national income to this equation, one can obtain a series for the formal sector productivity, i.e. $\theta_{F,t}$. Once this is obtained, the growth rate of shadow economy total factor productivity $\theta_{S,t}$ series is constructed assuming that it grows at a rate equal to the average of the formal sector productivity and physical capital. Together with the calibration of $\theta_{S,t}$ such that the shadow economy size in 2007 is equal to the value reported in Buehn and Schneider (2012) one obtains a full series for $\theta_{S,t}$ Once this series is obtained we use the equation above, defining shadow labor to back out the shadow labor series and finally with these series, the shadow economy size as % of GDP can easily be calculated.

Figure 2. Shadow Economy Size in Turkey: MIMIC vs. DGE



Figures 2 and 3 illustrate the behavior of the two series (MIMIC vs. DGE) both for Turkey and Austria from 1999 to 2010. For Turkey, both series are strongly positively correlated with each other (0.86). For Austria, excluding the last year (2010) the correlation between the two series is 0.75; however the striking jump of the Austrian shadow economy in 2010 according to the MIMIC estimate makes the overall correlation equal to about -0.09.

Figure 3. Shadow Economy Size in Austria: MIMIC vs. DGE

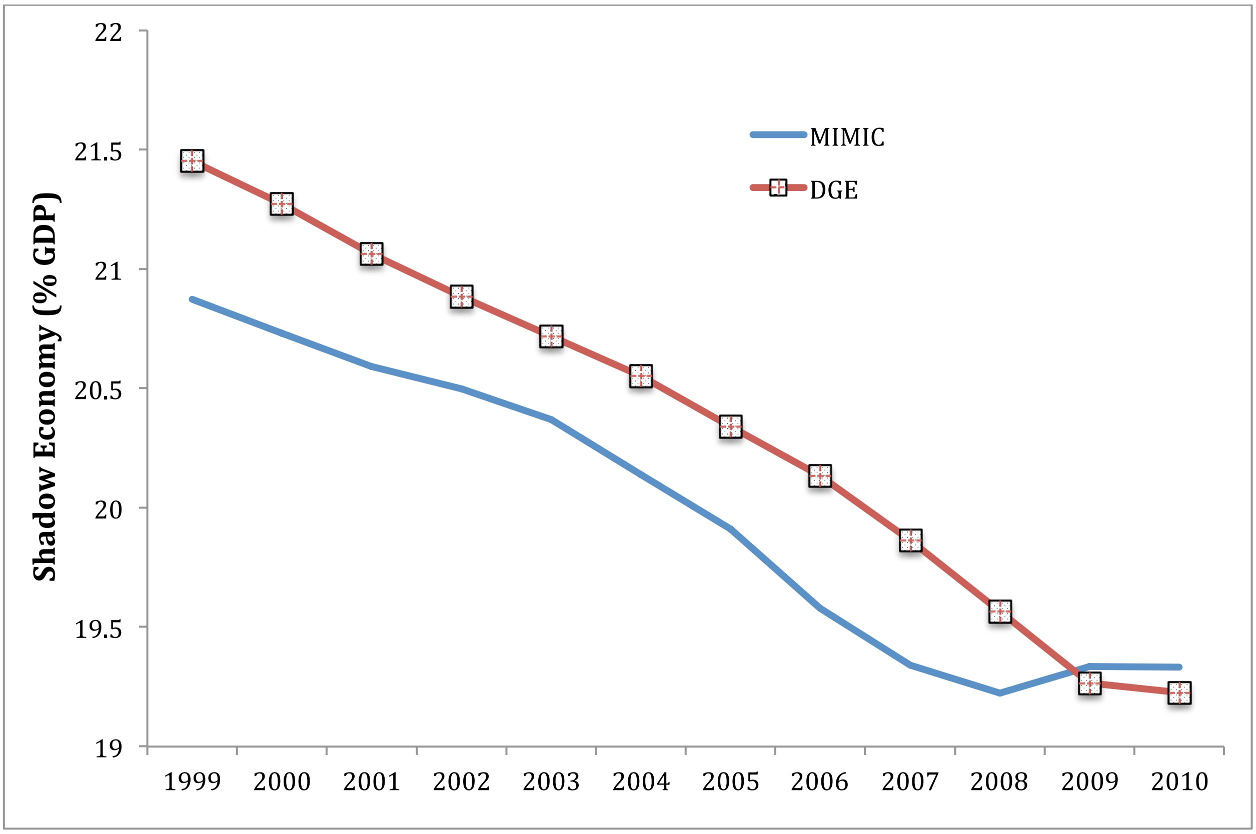


3. SHADOW ECONOMY ESTIMATES

We have constructed shadow economy series using both the MIMIC and the DGE approaches for 38 OECD economies (See Table 1 for the list of countries.) from 1999 to 2010. As we have mentioned above, for the MIMIC methodology, we use the estimates reported in Buehn and Schneider (2013) and the DGE estimates are obtained from Elgin and Oztunali (2012). Table 2 reports descriptive summary statistics of both series for each of the 38 countries from 1999 to 2010 in our dataset. What we observe from Table 2 is that the two series, which are obtained using two different methodologies, are strikingly similar to each other with respect to the average values of the mean, standard deviation, minimum and maximum values of the shadow economy size estimates[9]. Even though, there are some differences on a country-by-country basis between the two series, the differences of these four statistics are not statistically significant when we compare them using a standard mean comparison t-test.

Figure 4. Average Shadow Economy Size (Unweighted) of 38 OECD-Countries

[9] One problem of this comparison is that Elgin and Oztunali (2012) calibrate their model to match the 2007 values reported in Buehn and Schneider (2012). This process might create a bias towards similar values of both series. However, the variations of both series are completely different.



Next, in Figure 4 we illustrate the evolution of the (unweighted) average shadow economy size across the period from 1999 to 2010 with both shadow economy series. As evident from the figure, there is a secularly declining trend of shadow economy size over the 12 years; however the pace of the decline is larger in the DGE series compared to the MIMIC estimations. Moreover, in the MIMIC series there is an increase of the average shadow economy size after the crisis in 2008; which we don't observe in the DGE series. Even though the DGE the rate of the reduction of the shadow economy size in the DGE series is significantly decreased in 2008, we don't observe an increase in the estimate for this year.

As looking at unweighted series might be a misleading way of calculating the shadow economy size in a group of countries, in Figure 5 we plot the evolution of the GDP-weighted average shadow economy size in our 38-country group. As ceteris paribus, richer countries tend to have a smaller shadow economy (tough the relationship is not totally linear) once we weight the shadow economy size with GDP, the group average is significantly reduced.

Figure 5. Average Shadow Economy Size (GDP - weighted) of 38 OECD-Countries

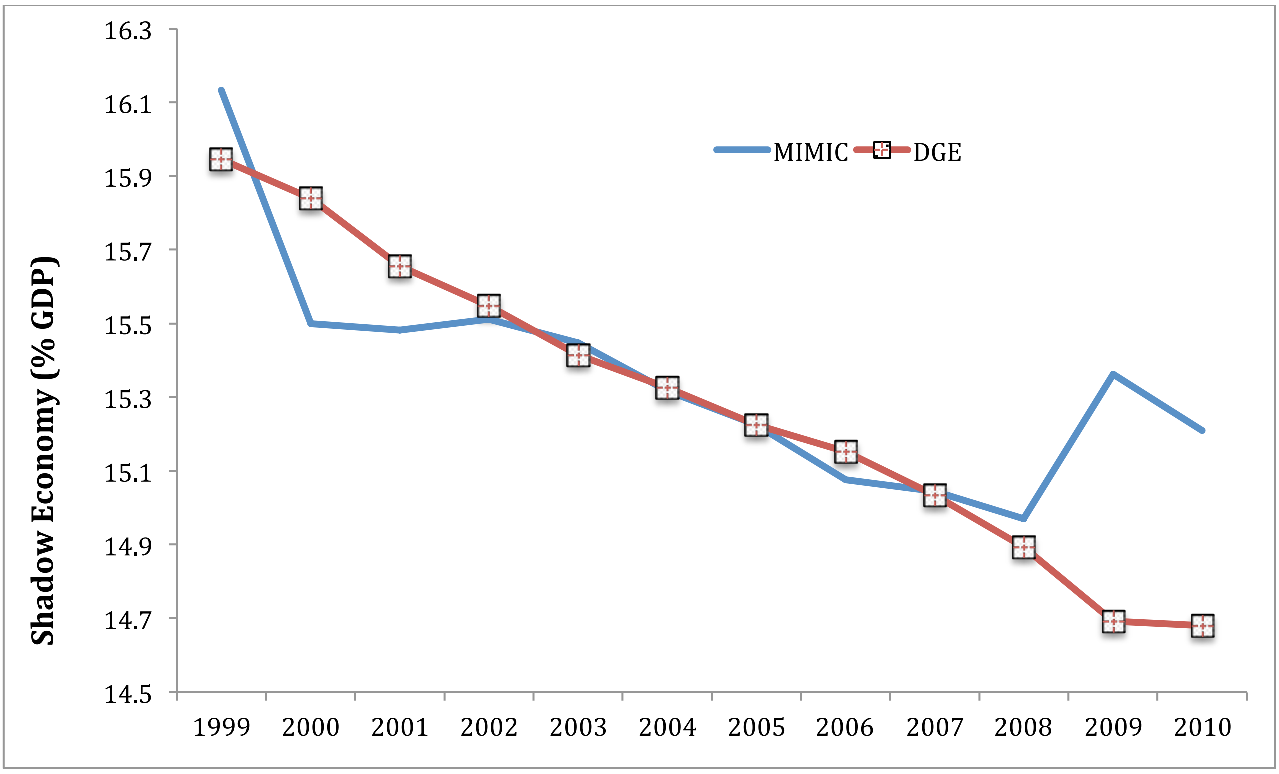


Figure 5 also reveals a striking difference between the two series considered. Even though, similar to the unweighted series, both the DGE and MIMIC series tend to have a declining trend over the period of analysis, the MIMIC series is less smooth and has a significantly higher standard deviation compared to it unweighted counterpart. Especially, the jump of the average shadow economy size after 2008 becomes more obvious in this case. This suggests that the countercyclicality of the shadow economy (as suggested by Elgin, 2012) throughout the crises years is more evident in the MIMIC series compared to the DGE one.

4. DRIVING FORCES OF SHADOW ECONOMIES

Similar to Buehn and Schneider (2013) we present the relative impacts of the causal variables on both of the shadow economy series in tables 3 and 4. Similar to the cited paper, we examine effects of seven variables on shadow economy size. These are personal income tax, indirect taxes (both as % of GDP), tax morale, unemployment rate, self-employment ratio, growth of real GDP per-capita and business freedom index. The sources of these series as well as the direction of their effects on shadow economy size are presented in Table 5.

Here we borrow the driving force estimates from the MIMIC approach from Buehn and Schneider (2013). In this paper, to obtain the relative effects of the driving forces of the shadow economies, the authors use the standardized coefficients of the causal variables from the MIMIC model they estimate to construct the shadow economy estimates. (See the cited paper for more details.) In order to obtain comparable estimates for the driving forces under the DGE approach, similar to the standardized coefficients used under the MIMIC approach, we simply obtain the coefficients by regressing the shadow economy series on the causal variables.

The estimates obtained using the MIMIC model imply that personal income tax (13.8 %), indirect taxes (14.1 %), tax morale (14.5 %), unemployment (14.7 %), self-employment (14.5 %), growth of GDP (14. 3 %) and business freedom index (14. 2 %) contribute more or less evenly to shadow economies. However, according to the estimates constructed using the DGE model growth of GDP per-capita has by far the largest effect (24. 7%) followed by indirect taxes (18. 5 %), unemployment (18.3 %), tax morale (17.1 %), personal income tax (11.2 %), self-employment (5.8 %), and business freedom index (4.3 %). These numbers indicate that the even though two methods produce shadow economy estimates highly similar in levels, the implied driving forces are strikingly different.

At this point, one important question would be whether there are any specific factors that might affect the relative contributions of the causal variables on shadow economy size as well as to the difference in the relative contributions of the two series we use. To this end, we conduct a simple regression analysis by regressing the average relative contribution of each driving force on several variables that might be associated with these. The variables we use as regressors are the capital-output ratio, government spending (as % of GDP), GDP per-capita (in constant 2005 USD) bureaucratic quality index and the democratic accountability index.[10] Table 6 presents the outputs of these regressions. The top panel uses driving forces from the MIMIC approach whereas the bottom panel uses the ones from the DGE. Table 6 illustrates several interesting facts. According to the results presented in the top panel, a larger capital-output ratio is associated with a higher contribution of the growth of GDP per-capita and tax morale to shadow economies as measured by the MIMIC ap-

[10] Capital-output ratio is calculated using data from Penn World Tables 7.1 (PWT) along with the perpetual inventory method. Similarly, we have obtained government spending (as % of GDP) from PWT: GDP per-capita is obtained from WDI and finally the two institutional quality indices, i.e. bureaucratic quality and democratic accountability indices are extracted from the International Country Risk Guide of the PRS Group.

porach, whereas a higher democratic accountability index (GDP per-capita) is associated with a lower contribution of the growth of GDP per-capita (tax morale) to shadow economies. Next, according to the results presented in the bottom panel, a larger capital-output ratio and GDP per-capita is associated with a larger contribution, whereas a larger democratic accountability index is associated with a smaller contribution of the growth of GDP per-capita to shadow economies. Similarly, a larger capital-output ratio is associated with a smaller contribution of the indirect taxes, and a larger GDP per-capita with a smaller contribution of tax morale to shadow economies. All these results indicate that the differences in the relative contributions of the driving forces are systematic and correlated with certain macroeconomic and institutional characteristics of national economies.

5. SUMMARY AND CONCLUSIONS

In this paper we compared the level and the driving forces of the shadow economies in 38 OECD countries using two different estimation methodologies. The first estimation procedure is the multiple-indicators-multiple-causes (MIMIC) approach which is based on an estimation of a structural equation model. The second estimation procedure is based on a two-sector dynamic general equilibrium (DGE) model, which was developed by Elgin and Oztunali. For both models we got estimates over the period 1999 to 2010 for 38 OECD countries. The driving forces obtained using the MIMIC model show that the personal income tax (13.8 %), indirect taxes (14.1 %), tax morale (14.5 %), unemployment (14.7 %), self-employment (14.5 %), GDP growth (14.3 %) and the business freedom index (14.2 %) contribute more or less evenly to the shadow economies. Opposite to this result, according to the estimates constructed using the DGE model (the driving forces of the shadow economy), growth of GDP per capita has by far the largest effect (24.7 %), followed by indirect taxes (18.5 %), unemployment (18.3 %), tax morale (17.1 %), personal income tax (11.2 %), self-employment (5.8 %) and the business freedom index (4.3 %).

Considering the size of the shadow economy using the two models, the size follows a similar pattern. There is more or less a steady decline from the year 1999 up to the year 2008 and with the MIMIC estimates then comes an increase and then a further decline. With the DGE estimates there is a decline up to the year 2010.

What type of conclusions can we draw from this comparison?

(1) The size of the shadow economies using these two approaches is very similar and its trend (a declining one over the period 1999 to 2010) is also reached by the two estimation procedures. The MIMIC estimation procedure is somewhat more sensitive to cyclical fluctuations because the shadow economy increases by the MIMIC estimations in the years 2008 and 2009 for the 38 countries.

(2) An interesting result is the similar pattern of the size of the shadow economy but a quite different pattern of the driving forces of the shadow economy using the two estimation methods.

(3) In order to detect these differences in the driving forces a more careful study for single OECD countries is necessary to see, what is the reason for that.

TABLES

Table 1: OECD countries included in the sample; estimation period: 1999–2010

Australia, Austria, Belgium, Bulgaria, Canada, Chile, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Korea, Latvia, Lithuania, Luxembourg, Malta, Mexico, Netherlands. New Zealand, Norway, Poland, Portugal, Romania, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Turkey, United Kingdom, United States

Table 2: Shadow Economy Size (Descriptive Statistics): MIMIC and DGE series from 1999 to 2010

Country	MIMIC				DGE			
	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
Australia	13.83	0.38	13.2	14.4	13.93	0.63	12.93	14.82
Austria	9.82	0.28	9.5	10.6	9.6	0.18	9.36	9.91
Belgium	21.53	0.77	20.3	22.7	21.57	0.51	20.77	22.41
Bulgaria	34.64	1.87	31.9	37.3	33.41	1.52	30.52	34.79
Canada	15.59	0.38	14.9	16.3	15.75	0.65	14.74	16.67
Chile	19.40	0.59	18.4	20.5	19.11	0.9	17.74	20.46
Cyprus	27.71	0.96	25.4	29.2	26.58	0.45	25.69	26.98
Czech Republic	17.58	1.53	15.2	19.3	17.3	0.54	16.44	18.02
Denmark	17.25	0.98	15.3	18.4	17.35	0.64	16.47	18.39
Estonia	23.66	1.44	20.8	25.6	27.7	1.99	25.98	30.12
Finland	17.38	0.65	16.4	18.4	17.31	0.53	16.52	18.07
France	14.84	0.43	14	15.7	14.96	0.41	14.35	15.59
Germany	15.68	0.6	14.6	16.4	15.31	0.15	15.11	15.63
Greece	27.00	1.2	25.1	28.7	27.19	1.03	25.74	28.82
Hungary	24.08	0.78	23.1	25.4	24.24	0.71	23.29	25.4
Iceland	15.21	0.75	13.8	16	15.58	0.81	14.3	16.63
Ireland	16.04	0.52	15.5	17.5	15.96	0.83	14.86	17.37
Italy	26.93	0.33	26.5	27.8	27.25	0.62	26.42	28.22
Republic of Korea	26.34	1.12	24.5	28.3	26.48	1.25	24.71	28.41
Latvia	22.12	1.22	20	23.9	24.77	2.01	20.85	27.12
Lithuania	25.43	1.24	23.6	27.2	28.42	1.76	25.09	31.04

Country	MIMIC				DGE			
	Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
Luxembourg	9.63	0.27	9.1	10	9.62	0.35	9.12	10.16
Malta	27.26	0.38	26.7	28.1	26.42	0.15	26.2	26.73
Mexico	30.00	0.54	28.8	30.8	29.61	0.64	28.81	30.87
Netherlands	13.16	0.22	12.7	13.6	13.15	0.29	12.7	13.66
New Zealand	12.25	0.37	11.8	13	12.34	0.46	11.69	13
Norway	18.59	0.48	17.7	19.2	18.28	0.54	17.33	19.03
Poland	26.44	1.43	23.8	27.7	26.7	1.19	24.83	28.59
Portugal	22.68	0.46	21.9	23.3	23.53	0.79	22.63	25.07
Romania	32.19	1.51	30	34.4	30.27	0.75	28.81	31.02
Slovak Republic	17.55	1.23	15.8	18.9	17.06	0.42	16.38	17.51
Slovenia	25.71	1.26	23.5	27.3	25.42	1.31	23.4	27.45
Spain	22.78	0.65	22.3	24.5	22.72	0.76	21.59	23.92
Sweden	18.55	0.59	17.7	19.6	18.08	0.42	17.41	18.67
Switzerland	8.32	0.48	7.2	8.8	8.13	0.06	8.05	0.23
Turkey	30.61	1.72	28	32.8	30.40	1.7	27.66	32.58
United Kingdom	12.48	0.27	12	12.9	12.48	0.44	11.9	13.21
United States	8.74	0.25	8.4	9.3	8.66	0.35	8.24	9.27
Average	20.24	0.79	18.93	21.42	20.33	0.76	19.17	21.21

Source: Authors' calculations

Table 3: Average relative impact (in %) of the causal variables on the shadow economy (MIMIC) of 38 OECD countries over 1999 to 2010

Country	Average size of the shadow economy	Personal income tax	Indirect taxes	Tax morale	Unemployment	Self-employment	GDP growth	Business freedom
Australia	13.8	12.4	13.4	14.1	18.1	15.8	13.2	13.0
Austria	9.8	12.4	14.6	14.1	11.8	16.8	15.9	14.4
Belgium	21.5	12.9	12.8	14.4	16.2	16.0	14.2	13.3
Bulgaria	34.6	14.9	13.5	14.8	14.8	14.2	13.7	14.2
Canada	15.6	12.7	14.9	14.9	18.4	11.7	13.8	13.6
Chile	19.4	16.1	14.1	14.1	14.2	12.9	14.4	14.3
Cyprus	27.2	13.8	14.5	14.5	14.3	14.5	13.8	14.6
Czech Rep.	17.6	15.1	16.0	14.0	11.5	13.1	14.3	15.9
Denmark	17.3	10.8	13.1	14.7	18.2	15.6	14.4	13.2
Estonia	23.7	16.4	14.4	14.5	12.4	13.1	14.0	15.2
Finland	17.4	15.4	13.0	14.8	12.9	16.9	13.7	13.3
France	14.8	9.1	14.4	14.8	15.1	17.3	15.1	14.3
Germany	15.7	16.6	13.2	15.0	13.0	12.8	15.2	14.2
Greece	27.0	10.3	16.2	14.5	10.4	18.7	14.3	15.5
Hungary	24.1	14.0	14.1	15.0	15.0	14.2	13.5	14.2
Iceland	15.2	12.4	14.3	14.7	15.1	14.4	14.8	14.3
Ireland	16.0	13.7	13.9	14.3	18.0	12.5	13.7	14.0
Italy	26.9	13.0	13.9	14.0	14.5	14.0	16.6	13.9
Korea	26.3	13.3	14.4	14.9	13.3	14.6	15.3	14.2
Latvia	22.2	14.6	14.3	13.9	15.1	14.6	13.3	14.2
Lithuania	25.4	13.1	14.5	14.1	15.1	14.5	14.2	14.5
Luxembourg	9.6	14.7	14.3	14.2	13.0	14.9	14.5	14.3
Malta	27.3	14.3	14.3	15.1	14.3	14.3	13.4	14.3
Mexico	30.0	14.3	13.7	14.5	14.4	14.2	14.9	13.9
Netherlands	13.2	14.6	13.6	14.0	16.1	13.7	14.2	13.8
New Zealand	12.2	14.6	14.2	14.2	15.2	14.3	13.2	14.2
Norway	18.6	14.1	13.8	14.2	14.1	14.5	15.4	13.9
Poland	26.4	14.1	14.4	14.4	14.2	14.5	14.1	14.4
Portugal	22.7	12.5	14.1	14.9	14.2	14.4	15.9	14.1
Romania	32.2	15.5	14.2	13.9	14.2	14.1	14.0	14.2
Slovak Rep.	17.5	15.0	14.7	14.7	14.4	14.4	12.0	14.8

Country	Average size of the shadow economy	Personal income tax	Indirect taxes	Tax morale	Unemployment	Self-employployment	GDP growth	Business freedom
Slovenia	25.2	14.4	14.3	14.4	14.8	14.4	13.2	14.4
Spain	22.8	11.2	13.6	14.6	17.5	16.4	13.8	12.9
Sweden	18.6	14.9	14.3	14.6	13.3	14.2	14.2	14.5
Switzerland	8.3	13.8	13.0	15.7	13.4	14.4	14.8	14.8
Turkey	30.6	13.9	14.1	14.5	13.7	14.5	15.1	14.3
United Kingdom	12.5	13.6	14.0	14.3	18.1	12.4	13.7	14.0
United States	8.7	13.9	14.1	13.7	14.9	14.4	15.0	14.1
Average	20.2	13.8	14.1	14.5	14.7	14.5	14.3	14.2

Source: Schneider and Buehn (2013)

Table 4: Average relative impact (in %) of the causal variables on the shadow economy (DGE) of 38 OECD countries over 1999 to 2010

Country	**Average size of the shadow economy**	**Personal income tax**	**Indirect taxes**	**Tax morale**	**Unemployment**	**Self-employment**	**GDP growth**	**Business freedom**
Australia	13.9	10.1	17.6	16.7	22.6	6.3	22.8	3.9
Austria	9.6	10.1	19.1	16.7	14.7	6.7	28.2	4.4
Belgium	21.6	10.5	16.8	17.0	20.2	6.4	25.0	4.0
Bulgaria	33.4	12.2	17.7	17.5	18.5	5.7	24.2	4.3
Canada	15.8	10.4	19.5	17.6	23.0	4.7	20.7	4.1
Chile	19.1	13.2	18.5	16.7	17.7	5.2	24.5	4.3
Cyprus	26.6	11.3	19.0	17.1	17.8	5.8	24.5	4.4
Czech Rep.	17.3	12.3	21.0	16.6	14.4	5.2	25.7	4.8
Denmark	17.4	8.8	17.2	17.4	22.7	6.2	23.7	4.0
Estonia	31.2	13.4	18.9	17.1	15.5	5.2	25.2	4.6
Finland	17.3	12.6	17.0	17.5	16.1	6.8	26.0	4.0
France	15.0	7.4	18.9	17.5	18.8	6.9	26.1	4.3
Germany	15.3	13.6	17.3	17.7	16.2	5.1	25.7	4.3
Greece	27.2	8.4	21.2	17.1	13.0	7.5	28.0	4.7
Hungary	24.2	11.4	18.5	17.7	18.7	5.7	23.6	4.3
Iceland	15.6	10.1	18.7	17.4	18.8	5.8	24.8	4.3
Ireland	16.0	11.2	18.2	16.9	22.5	5.0	22.0	4.2
Italy	27.2	10.6	18.2	16.6	18.1	5.6	26.7	4.2
Korea	26.5	10.9	18.9	17.6	16.6	5.8	25.9	4.3
Latvia	29.3	11.9	18.7	16.4	18.8	5.8	23.9	4.3
Lithuania	31.4	10.7	19.0	16.7	18.8	5.8	24.6	4.4
Luxembourg	9.6	12.0	18.7	16.8	16.2	6.0	25.9	4.3
Malta	26.4	11.7	18.7	17.9	17.8	5.7	23.8	4.3
Mexico	29.6	11.7	18.0	17.1	18.0	5.7	25.3	4.2
Netherlands	13.2	11.9	17.8	16.6	20.1	5.5	23.9	4.2
New Zealand	12.3	11.9	18.6	16.8	19.0	5.7	23.7	4.3
Norway	18.3	11.5	18.1	16.8	17.6	5.8	26.0	4.2
Poland	26.7	11.5	18.9	17.0	17.7	5.8	24.7	4.4
Portugal	23.5	10.2	18.5	17.6	17.7	5.8	25.9	4.3
Romania	30.3	12.7	18.6	16.4	17.7	5.6	24.6	4.3
Slovak Rep.	17.1	12.3	19.3	17.4	18.0	5.8	22.9	4.5
Slovenia	25.4	11.8	18.7	17.0	18.5	5.8	23.9	4.4
Spain	22.7	9.2	17.8	17.3	21.8	6.6	23.4	3.9

Country	Average size of the shadow economy	Personal income tax	Indirect taxes	Tax morale	Unemployment	Self-employment	GDP growth	Business freedom
Sweden	18.1	12.2	18.7	17.3	16.6	5.7	25.1	4.4
Switzerland	8.1	11.3	17.0	18.6	16.7	5.8	26.1	4.5
Turkey	30.4	11.4	18.5	17.1	17.1	5.8	25.8	4.3
United Kingdom	12.5	11.1	18.4	16.9	22.6	5.0	21.8	4.2
United States	8.7	11.4	18.5	16.2	18.6	5.8	25.3	4.3
Average	20.6	11.2	18.5	17.1	18.3	5.8	24.7	4.3

Source: Elgin and Oztunali (2012)

Table 5: Causal Variables of Shadow Economies

Causal Variable	**Description and source**	**Expected sign**
Business freedom	Business freedom index measuring the time and efforts of business activity ranging; 0 = least business freedom, and 100 = maximum business freedom; Heritage Foundation	-
GDP growth	GDP per capita growth, annual (%); WDI	+/-
Indirect taxes	Taxes on goods and services (% of total tax revenue); WDI	+
Personal income tax	Personal Income Tax (PIT) to GDP, Government Finance Statistics; International Monetary Fund	+
Self-employment	Total self-employed workers (proportion of total employment); WDI	+
Tax morale	To assess the level of tax morale we use the following question: *‘‘Please tell me for each of the following statements whether you think it can always be justified, never be justified, or something in between: . . . Cheating on tax if you have the chance’’.* The question leads to a 10-scale index of tax morale with the two extreme points ‘‘never justified’’ (1) and ‘‘always justified’’ (10). Using the proportion of respondents who answered the question with a value of 6 or higher, higher values of our tax morale variable indicate a lower level of tax moral; European and World Value Surveys	-
Unemployment	Unemployment rate (% of total labor force; WDI	+

Currency in circulation	Monetary aggregates M0 over M1; International Monetary Fund, International Financial Statistics	+
GDP pc	GDP per capita, PPP (constant 2005 international $); WDI	-
Labour force participation	Labor force participation rate (% of total population); WDI	-

Table 6: Determinants of the Driving Forces of Shadow Economies

Dep. Var.:	Growth	Indirect	Unemp.	Morale	Business	Self-Emp.	PIT
Regressor							
Capital	1.14*	-0.56	-1.19	0.41***	-0.08	0.82	-0.60
	(3.27)	(1.62)	(1.35)	(1.71)	(0.33)	(1.16)	(0.94)
Gov	-0.05	-0.05	0.10	-0.01	-0.03	0.08	-0.03
	(0.91)	(1.00)	(1.27)	(0.37)	(1.14)	(0.94)	(0.29)
GDP	0.02	-0.006	-0.01	-0.01**	-0.0004	0.01	-0.01
	(1.44)	(1.07)	(0.51)	(2.19)	(0.08)	(1.13)	(0.46)
Bur.	-0.02	-0.35	0.38	0.22	-0.13	-0.17	0.04
	(0.23)	(1.61)	(0.68)	(1.16)	(0.81)	(0.32)	(0.05)
Dem.	-1.05*	0.37	0.82	0.11	0.005	0.15	-0.39
	(2.85)	(1.25)	(1.04)	(0.53)	(0.05)	(0.21)	(0.49)
R-squared	0.48	0.14	0.14	0.15	0.07	0.08	0.06
Observations	38	38	38	38	38	38	38
Dep. Var.:	Growth	Indirect	Unemp.	Morale	Business	Self-Emp.	PIT
Regressor							
Capital	2.05*	-0.79***	-1.52	0.40	-0.04	0.31	-0.40
	(3.17)	(1.78)	(1.48)	(1.43)	(0.58)	(1.14)	(0.79)
Gov	-0.02	-0.07	0.12	-0.03	-0.02	0.03	-0.02
	(0.31)	(1.15)	(1.29)	(0.62)	(1.35)	(0.89)	(0.09)
GDP	0.03**	-0.009	-0.02	-0.02**	-0.0005	0.005	-0.01
	(2.10)	(1.09)	(0.50)	(2.29)	(0.03)	(1.16)	(0.46)
Bur.	-0.21	-0.46	0.48	0.26	-0.04	-0.07	0.03
	(0.46)	(1.62)	(0.68)	(1.22)	(0.83)	(0.32)	(0.04)
Dem.	-1.45**	0.52	1.04	0.17	0.01	0.07	-0.37
	(2.07)	(1.37)	(1.10)	(0.73)	(0.22)	(0.26)	(0.58)
R-squared	0.32	0.16	0.14	0.21	0.07	0.08	0.05
Observations	38	38	38	38	38	38	38

The top panel uses driving forces from the MIMIC approach whereas the bottom panel uses the ones from the DGE. Absolute values of robust t-statistics are reported in parentheses. *, **, *** denote 1, 5 and 10% confidence levels, respectively. In all regressions a constant is also included but not reported.

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