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25 November 2008

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Abstract: We analyze how adding the shadow economy to official output figures affects estimated technical efficiency at the country level. We find that this only slightly affects the ranking of efficiency scores, but increases average efficiency in a sample of 87 to 97 countries, both developed and developing. Our results are robust to the functional form of the production technology and the adjustment of labour to account for years of schooling.

Running title: The shadow economy and aggregate efficiency.

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1. Introduction

Most studies of economic development rest on official output figures. However, in so doing they neglect a sizeable part of economic activity, which takes place in the informal sector, and therefore goes unrecorded in official statistics. Nevertheless, as Tanzi (1999) remarks, though some of those activities may be illegal, others are legal and socially valuable. They should therefore be taken into account when measuring a country's output. Moreover, the capacity of the informal sector to "provide goods and services for a large though often poor section of the population" (ILO, 1972) was recognized early, and repeatedly emphasized thereafter. Livingstone (1991) for instance points out that the informal sector provides cheap and appropriate goods to markets quantitatively dominated by poor consumers.

Furthermore, those activities may also be important from a quantitative point of view. Thus, according to Schneider (2005), the "shadow economy", defined as currently unregistered economic activities that contribute to the officially calculated (or observed) Gross National Product, amounted to 16 percent of official output in OECD countries, 39 percent in developing countries, and up to 40 percent in transition countries, in 2002/2003.

Those daunting figures call into question the interpretation of the results of empirical studies that ignore this phenomenon, because poorer countries are also known to be less productive, as Hall and Jones (1999) show, and to exhibit larger shadow economies, as most studies on the determinants of the shadow economy show, like Johnson et al. (1998a) or Schneider and Enste (2000). In particular, assessments of productivity at the aggregate

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country level, like e.g. Collins et al. (1996), Klenow and Rodriguez-Clare (1997), Prescott (1998), Caselli (2005), or Kneller and Stevens (2003), are likely to be affected when ignoring the shadow economy.

This is particularly important for efficiency frontier methods such as stochastic frontier analysis (SFA), which estimates the world's production frontier and assesses countries' aggregate efficiency relative to that frontier (see e.g. Adkins et al., 2002, or Kneller and Stevens, 2003). Ignoring a substantial share of output is likely to result in biased estimates of the production frontier and a mismeasurement of inefficiencies. Most likely, efficiency is underestimated in countries with big shadow economies. The extent of the bias, however, is an empirical matter.

In what follows, we therefore check the robustness of the SFA to the inclusion of the shadow economy in official output figures. We first follow Kneller and Stevens (2003) and estimate the world production frontier based on official output figures. We then add the shadow output to gauge the bias of existing studies. The rest of the paper is therefore organised as follows. Next section presents our empirical strategy. The following section displays and comments our results. The last section concludes.

2. Empirical strategy

In this section, we first present the various models that we estimated. We then describe the datasets on which they were estimated and how output figures were corrected.

2.1. The models

We apply the stochastic frontier approach to measure technical efficiency at the aggregate level. Technical efficiency measures how close a country's production is to what a country's optimal production would be for using the same bundle of inputs. Adkins et al. (2002) or Méon and Weill (2004, 2005), among others, adopted the same approach to evaluate the relationship of aggregate technical efficiency with institutional variables.[1] Its basic concept is illustrated in figure 1 below. A production frontier is estimated with the stochastic frontier approach, providing a benchmark for each country regardless of its inputs.

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[1] As an anonymous referee pointed out, by estimating and aggregate production frontier, we overlook the impact of countries' sectorial composition. However, in his survey, Caselli (2005) shows that distinguishing sectors within countries does not improve our understanding of cross-country TFP differences. Moreover by considering countries' total outputs and factor endowments, our efficiency scores also measure the efficiency of those countries' specialisations.

Then, the efficiency score is computed by comparing the optimal output per worker with the effective output per worker.

Figure 1: The efficiency frontier
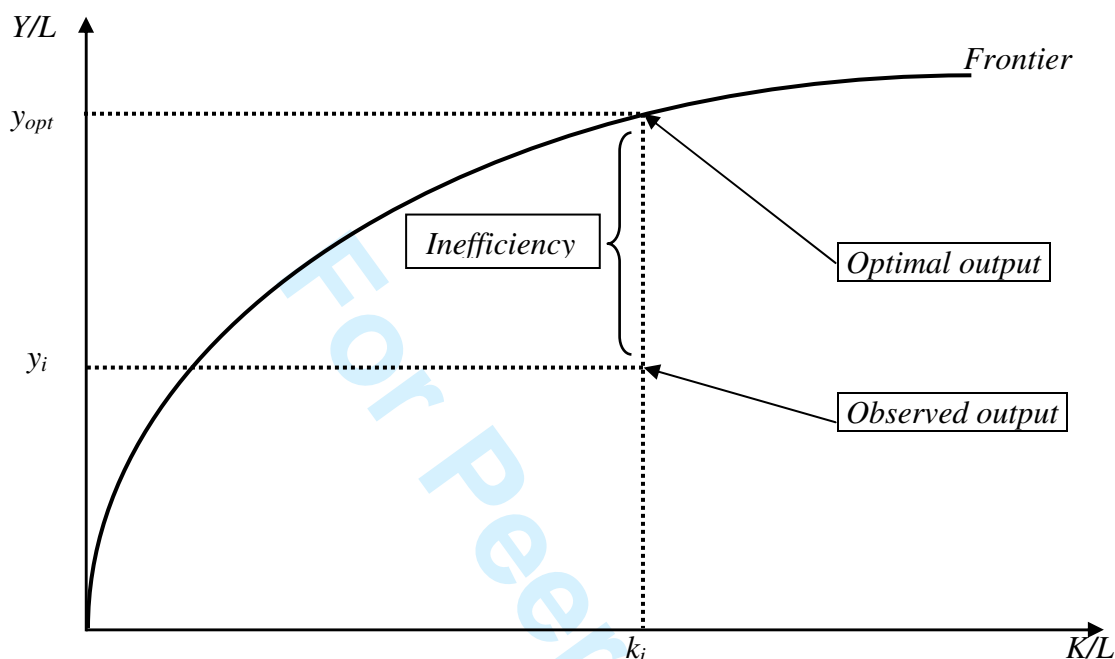
y output per worker, *k* capital per worker, *Y* output, *K* capital, *L* labour

There are several reasons why macroeconomic performance is better measured using this approach than more usual performance indicators, like total factor productivity. First, it provides synthetic measures of performance. Namely, unlike productivity measures such as per capita income or output per worker, efficiency scores computed with the stochastic frontier approach allow to include several input dimensions in the evaluation of performances. As a result, output can not only be compared to the labour stock, but also to the stocks of physical capital and human capital.

Second, technical efficiency provides relative measures of performance. Namely, once a production frontier is estimated, each country can be compared to the best-practice countries. As a result, the efficiency score assesses how close each country's production is to what a hypothetical country's optimal production would be for using the same bundle of inputs. It thus directly provides a relative measure of performance.

Third, whereas total factor productivity measures assess performance by the whole residual from the production frontier for each country, stochastic frontier approach allows to

disentangle the distance to the production frontier between an inefficiency term and a random error, taking exogenous events into account. In other words, it decomposes the residual into an efficiency component and a white noise component that may reflect bad luck or measurement errors.

In order to estimate the production frontier, we need to specify its functional form. For the sake of brevity, we consider the most common production functions analyzed in the development accounting literature, namely the Cobb-Douglas function. We complement it by the translog function. Those specifications respectively read:

$$\ln(Y_i) = \beta_0 + \beta_1 \ln(K_i) + \beta_2 \ln(L_i) + v_i - u_i \tag{1}$$

$$\ln(Y_i) = \beta_0 + \beta_1 \ln(K_i) + \beta_2 \ln(L_i) + \beta_3 \ln(K_i)^2 + \beta_4 \ln(L_i)^2 + \beta_5 \ln(K_i) \ln(L_i) + v_i - u_i \tag{2}$$

where Y_i measures country i's output, K_i its capital stock, and L_i its labour force. v_i is the above-mentioned white noise component of the residual accounting for measurement errors or unpredictable events that make the frontier random. It is assumed to have a normal distribution with zero mean and variance σ_v^2. u_i is the inefficiency term. It is a one-sided component with variance σ_u^2. As is common in the literature, we assume a half-normal distribution for the inefficiency term. We estimate the production frontier by maximum likelihood methods using the software program Frontier 4.1.

The Cobb-Douglas function is by far the most common in the development accounting and the aggregate efficiency literatures (see e.g. King and Levine, 1994, Klenow and Rodriguez-Clare, 1997, Hall and Jones, 1999, or Prescott, 1998, for the development accounting literature, and Adkins et al., 2002, or Méon and Weill, 2005 for the aggregate efficiency literature) . However, estimating a translog function in addition to the standard Cobb-Douglas allows to statistically compare the performance of the two specifications.

2.2. Official data

We use Caselli's (2005) database, which provides the most comprehensive and up to date figures for development accounting. It provides data on official output, physical capital stocks, and human capital stocks. Capital stock figures are computed from the Penn World Tables mark 6.1, and are available for 1996. They are based on the perpetual inventory method. That method computes a period's capital stock according to the following equation:

$$K_t = (1 - \delta)K_{t-1} + I_t \tag{3}$$

Where I_t is investment and δ is the depreciation rate, which is assumed to be equal to 0.06.[2] The capital stock in the base year is computed as $I_0 / (g + d)$, which is the steady state expression of the capital stock in the Solow growth model. I_0 is the first available value of investment, and g is the average geometric growth rate for the investment between the first year for which it is available and 1970.[3]

We use two different measures of the labour force. First, we define L_i as the absolute number of workers. Second, following Kneller and Stevens (2003) and Caselli (2005), we replace it by a measure of human capital-adjusted labour supply $L_i^* = H_iL_i$, where H_i is the mean years of schooling of the labour force.

2.3. Data on the shadow economy

The key element in the present paper is correcting output figures for the shadow economy. Data for the shadow economy are taken from Schneider (2006). He calculates the size and development of the shadow economy of 145 countries, including developing, transition, and highly developed OECD countries over the period 1999 to 2003, employing the MIMIC (multiple-indicators multiple-causes) and currency demand estimation technique.[4]

Figure 2: Development of the shadow economy.

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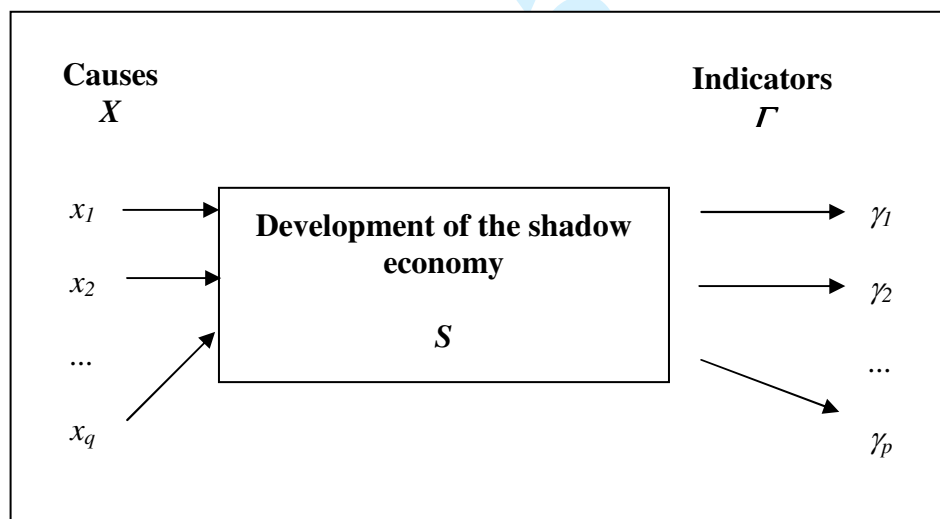
[2] This value is the standard value in the literature. Moreover, Caselli (2005) shows that the explanatory power of aggregate production functions is little affected when a different value is used.

[3] A thorough discussion of those assumptions can be found in Caselli (2005). He shows that the results of development accounting are robust to more refined assumptions.

[4] A critical survey of existing methods to estimate the shadow economy can be found in Schneider (2006).

The MIMIC method is based on the statistical theory of unobserved variables, which considers multiple causes and multiple indicators of the phenomenon to be measured. For the estimation, a factor-analytic approach is used to measure the hidden economy as an unobserved variable over time. The unknown coefficients are estimated in a set of structural equations within which the "unobserved" variable cannot be measured directly. The MIMIC model here consists of two parts. The measurement model links the unobserved variables to observed indicators.[5] The structural equations model specifies causal relationships among the unobserved variables. In this case, there is one unobserved variable: the size of the shadow economy. The model for one latent variable (S) can be described as follows:

Structural equation model:

$$S = \delta X + v \tag{4}$$

Measurement model:

$$\Gamma = \lambda S + \varepsilon \tag{5}$$

where S is the unobservable scalar latent variable (the size of the informal economy), $\Gamma = (\gamma_1 \ldots, \gamma_p)'$ is a vector of indicators for S, $X = (x_1, \ldots x_q)'$ is a vector of causes of S. λ and δ are the ($p\times1$) and ($q\times1$) vectors of parameters, and v and ε are respectively a scalar error and a ($p\times1$) error.

Equation (5) links the informal economy to its indicators or symptoms, while equation (4) associates the informal economy with its causes. Assuming that errors are normally distributed and mutually uncorrelated, the model can be solved by combining equations (4) and (5):

$$\Gamma = \pi X + \mu \tag{6}$$

where $\pi \equiv \lambda \delta$, and $\mu \equiv \lambda v + \varepsilon$.

Because Γ and X are observable data vectors, equation (6) can be estimated by maximum likelihood estimation using the restrictions implied in both the coefficient matrix π and the covariance matrix of the error μ.

Since the reduced form parameters of equation (6) remain unaltered when λ is multiplied by a scalar and Γ and σ_v^2 are divided by the same scalar, the estimation of (4) and (5) requires a normalization of the parameters in (4). A convenient way to achieve this is to constrain one element of λ to some pre-assigned value, usually 1.

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[5] One of the latest papers dealing extensively with the DYMIMIC approach, its development and its weaknesses is from Del'Anno (2003). One may also refer to the excellent study by Giles and Tedds (2002), as well as Breusch (2005a, 2005b).

Since the estimation of λ and δ is obtained by constraining one element of λ to some arbitrary value, it is useful to standardize the regression coefficients δ and λ as follows:

$$\hat{\delta}^{std} = \hat{\delta}(\hat{\sigma}_S/\hat{\sigma}_\Gamma) \tag{7a}$$

$$\hat{\lambda}^{std} = \hat{\lambda}(\hat{\sigma}_X/\hat{\sigma}_S) \tag{7b}$$

The standardized coefficient measures the expected change in the standard-deviation units of the dependent variable due to a one standard-deviation change of the given explanatory variable when the other variables are held constant.

Using the estimates of the $\hat{\delta}^{std}$ vector and setting the error term v to its mean value of zero, the predicted ordinal values for the informal economy (S) can be estimated thanks to equation (4).

Then, by using information regarding the specific value of informal activity for some country (if it is a cross country study) or for some point in time (if it is a time series study), obtained from some other source, the within-sample predictions for S can be converted into absolute series.

There is a large body of literature on the possible causes and indicators of the shadow economy.[6] That literature distinguishes three broad types of causes of the shadow economy. The first cause is the burden of direct and indirect taxation, both actual and perceived. A rising burden of taxation provides a strong incentive to work in the shadow economy to evade taxation. The second cause is the regulatory burden. The heavier it is, the larger the incentives to work in the shadow economy to avoid regulations. The last cause of the shadow economy hinges upon citizens' tax morale, which describes their attitude toward paying taxes. It determines the readiness of individuals to leave their official occupations and enter the shadow economy. It is assumed that a declining tax morale tends to increase the size of the shadow economy.

On the other hand, one may contend that the size of the shadow economy is reflected in three sets of indicators. The first is the development of monetary indicators. If activities in the shadow economy increase, additional monetary transactions are required. The second

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[6] Thomas (1992), Schneider (1994a, 1997, 2003, 2005), Pozo (1996), Johnson, et al. (1998a, 1998b), Giles (1997a, 1997b, 1999a, 1999b, 1999c), Giles and Tedds (2002), Giles et al. (2002), Del'Anno (2003), and Del'Anno and Schneider (2003).

indicator is the development of the labour market. Increasing participation of workers in the hidden sector results in a decrease in participation in the official economy. Similarly, increased activities in the hidden sector may be expected to be reflected in shorter working hours in the official economy. Third, the size of the shadow economy may also affect the development of the production market. An increase in the shadow economy means that inputs (especially labour) move out of the official economy. This displacement might reduce the growth rate of the official economy.

The latest use of the model approach has been undertaken by Giles (1999a, 1999b, 1999c) and by Giles et al. (2002), Giles and Tedds (2002), Chatterjee et al. (2003), and Bajada and Schneider (2005). They basically estimate a comprehensive (sometime dynamic) MIMIC model to get a time series index of the hidden/measured output of New Zealand, Canada, India or Australia, and then estimate a separate "cash-demand model" to obtain a benchmark for converting this index into percentage units. Overall, this latest combination of the currency demand and DYMIMIC approach clearly shows that some progress in the estimation technique of the shadow economy has been achieved and a number of critical points have been overcome.

Admittedly the (DY)MIMIC method has its own drawbacks. It has for instance been criticized for the instability of estimated coefficients with respect to sample size changes and alternative specifications. The difficulty to obtain reliable data on cause variables other than tax variables has been pointed out, and the reliability of variables grouping into "causes" and "indicators" in explaining the variability of the shadow economy has sometimes been questioned. However, that method provides the largest available and consistent data set on the extent of the shadow economy. Since we need to merge that dataset with several datasets, we need to start with the largest possible sample, which Schneider (2006)'s dataset allows.[7]

In our sample, the average size of the shadow economy is 34 percent. Merging our data leaves us with 87 observations when human capital is taken into account and 97 otherwise. Those samples are large, by the standards of macroeconomics. They include both developed and developing countries.[8] Summary statistics are presented in table 1 above.

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[7] Recall that Schneider's (2006) dataset provides estimates of the shadow economy for 145 countries. By contrast, Friedman et al. (2000) could only get estimates for 69 countries.
[8] The sample of 97 countries includes 23 OECD countries and 74 non-OECD countries. It is described in the Appendix.

Table 1: description of untransformed variables

Variable	Definition	Mean	Std. deviation
Y	Official output (billions of US$)	331.93	939.63
K	Capital stock (billions of US$)	721.77	2136.38
L	Number of workers (millions)	23349428.26	13.73
H	Average years of schooling	5.74	2.96
S	Shadow economy (percentage of Y)	33.65	8.60

Finally, we corrected output figures for the shadow economy. To do so, we added the shadow economy to official output figures. Corrected output figures are thus defined as the sum of official and shadow output such that $Y_i^* = (1+S_i)Y_i$, where S_i is the ratio of unofficial to official output in country i. As the oldest vintage of Schneider's estimates is 1999, we added that vintage to Caselli's dataset, which pertains to 1996. We accordingly worked with a cross-section of countries consisting of developed and developing countries for the late 1990s.

3. Results

To assess the impact of adding the shadow economy to official figures on measured aggregate efficiency, we estimate each model twice: once with raw output figures, and once with output figures corrected for the shadow economy.

Estimations 1a, 2a, 3a, 4a use official output and estimations 1b, 2b, 3b, 4b add the shadow economy to these output figures. The first four estimations refer to the Cobb-Douglas specification, while the last four refer to the translog function. Finally, models 1 and 3 use raw labour figures, while models 2 and 4 use human capital-adjusted labour supply. We thus end up estimating eight specifications, the results of which are displayed in tables 2a and 2b.

Table 2a: Stochastic frontier results: Cobb-Douglas

	Model 1		Model 2	
	Official output (1a)	Corrected output (1b)	Official output (2a)	Corrected output (2b)
Const.	2.874***	3.702***	4.306***	5.084***
	(6.93)	(8.72)	(8.88)	(10.70)
K	0.694***	0.657***	0.544***	0.516***
	(34.44)	(32.82)	(13.52)	(13.81)
L	0.299***	0.323***	0.416***	0.427***
	(10.24)	(11.13)	(8.52)	(8.95)
σ	0.132	0.119***	0.195***	0.172***
	(3.42)	(3.05)	(3.46)	(3.23)
γ	0.622***	0.536*	0.833***	0.711***
	(2.86)	(1.88)	(6.11)	(3.57)
log-likelihood	−14.39	−13.78	−17.47	−19.86
N	97	97	87	87

Absolute *t*-statistics in parentheses. The sigma statistics is defined as $\sigma = (\sigma_u^2 + \sigma_v^2)^{\frac{1}{2}}$. The gamma statistics is defined as $\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$. *, **, *** denote an estimate significantly different from 0 at the 10%, 5% or 1% level.

Not surprisingly, adding the shadow economy to official output produces different results across the two specifications of the production function. With the Cobb-Douglas specification, adding the shadow results in an increase of the production frontier's intercept. As corrected output is by construction greater than official output, the production frontier shifts upwards. However, the other coefficients remain similar in magnitude.

The table also shows that – contrary to the results of Kneller and Stevens (2003) – the translog specification does not outperform the Cobb-Douglas in our sample, as the log-likelihood ratios show. Moreover, the results obtained with the translog specification are less consistent. Namely, only the coefficient on labour is consistently significant, whereas other coefficients are insignificant, with the exception of the coefficient on physical capital in model 3, which turns significant when the shadow economy is added to official output. In addition, model 4 is the only specification whose goodness of fit deteriorates when the shadow economy is taken into account.

Table 2b: Stochastic frontier results: Translog

	Model 3		Model 4	
	Official output (3a)	Corrected output (3b)	Official output (4a)	Corrected output (4b)
Const.	2.266	0.322	6.112	5.398
	(0.54)	(0.08)	(1.44)	(1.20)
K	0.511	0.720**	0.161	0.286
	(1.55)	(2.16)	(0.37)	(0.62)
L	0.664*	0.645*	0.769*	0.727
	(1.94)	(1.88)	(1.73)	(1.53)
K^2	0.012	−0.002	0.001	−0.016
	(1.06)	(0.18)	(0.05)	(0.67)
L^2	0.008	−0.012	−0.024	−0.051
	(0.40)	(0.56)	(0.64)	(1.28)
K×L	−0.025	0.002	0.019	0.058
	(0.95)	(0.09)	(0.36)	(1.03)
σ	0.132***	0.118***	0.194***	0.169***
	(3.53)	(3.10)	(3.54)	(3.20)
γ	0.640***	0.543*	0.838***	0.711***
	(3.15)	(1.95)	(6.46)	(3.56)
log-likelihood	−13.55	−13.16	−16.89	−18.93
LL ratio	1.68	1.24	1.16	1.86
N	97	97	87	87

Absolute *t*-statistics in parentheses. The sigma statistics is defined as $\sigma = (\sigma_u^2 + \sigma_v^2)^{\frac{1}{2}}$. The gamma statistics is defined as $\gamma = \sigma_u^2 / (\sigma_u^2 + \sigma_v^2)$. *, **, *** denote an estimate significantly different from 0 at the 10%, 5% or 1% level.

What is more interesting though is the evolution of inefficiency scores when output is corrected for the shadow economy. Their summary statistics are displayed in table 3a and 3b. It appears that correcting output figures for the shadow economy results in an increase of the average and median efficiency scores. Thus, average and median distance to the frontier diminishes. The decrease in the gamma statistics displayed in table 2a and 2b, indicating a decreasing share of inefficiency in the estimations' total residuals, points to the same conclusion.

Table 3a: Descriptive statistics and correlation of raw and corrected efficiency scores:

Cobb-Douglas

	Model 1		Model 2	
	Official output (1a)	Corrected output (1b)	Official output (2a)	Corrected output (2b)
Minimum	0.444	0.539	0.355	0.41
Maximum	0.934	0.937	0.933	0.927
Mean	0.808	0.828	0.748	0.774
Median	0.826	0.835	0.787	0.800
Std. deviation	0.0802	0.0655	0.131	0.103
Pearson	-	0.964	-	0.959
Spearman	-	0.945	-	0.958

All correlations are significant at the one percent level.

Table 3b: Descriptive statistics and correlation of raw and corrected efficiency scores:

Translog

	Model 3		Model 4	
	Official output (3a)	Corrected output (3b)	Official output (4a)	Corrected output (4b)
Minimum	0.431	0.527	0.351	0.407
Maximum	0.934	0.937	0.936	0.93
Mean	0.806	0.827	0.748	0.776
Median	0.822	0.836	0.786	0.797
Std. deviation	0.0828	0.0663	0.132	0.102
Pearson	-	0.974	-	0.965
Spearman	-	0.955	-	0.963

All correlations are significant at the one percent level.

This result is not trivial since the efficiency frontier shifts upwards with the inclusion of the shadow economy. As efficiency is a relative measure, one could as well have witnessed a decrease in efficiency. The observed evolution of efficiency scores therefore implies that the distribution of output figures changes due to the inclusion of the shadow economy. More

precisely, countries that were initially farther from the frontier benefited relatively more from the addition of unofficial production than the rest of the sample. Accordingly, minimum efficiency scores increase more than maximum scores, and the standard deviation of efficiency scores decreases. Thus, neglecting the size of the shadow economy results in overestimating inefficiencies in less efficient countries, and, in terms of traditional development accounting, this amounts to overestimating the residual. This is in line with our a priori expectations.

However, the last two lines of tables 3a and 3b also show that the ranking of countries in terms of efficiency is little affected when average efficiency rises. To be more specific, the coefficient of correlation between efficiency scores computed with or without the shadow economy is always greater than 95 percent and is significant at the one-percent level. Similarly, the Spearman rank correlation coefficient (measuring the similarity in country rankings) exceeds 94 percent in all specifications and is also significant at the one percent level. One can therefore conclude that the ranking of countries in terms of efficiency does not dramatically depend on the inclusion of the shadow economy in output figures.

As a result of the strong rank correlation, the ranking of countries is little affected by the inclusion of the shadow economy in output figures. Nevertheless, the ranking of some countries can be markedly affected. With model 1, for instance, 10 countries experience a drop in their ranking by at least 10 positions.[9] At the same time, 12 countries improve their ranking by 10 positions or more.[10] Changes in rankings are similar with other models.

4. Concluding remarks

In this paper, we analyzed the impact of adding the shadow economy to official output figures on estimated production functions and technical efficiency across up to 97 countries. Including the shadow economy hardly affects the ranking of countries in terms of efficiency. However, it results in an increase of observed efficiency scores. Adding the shadow economy to official output figures thus allows a more precise estimate of countries' outputs.

Those results are important in several respects. First, they show that estimates of the production function based on total output differ from those based on official output figures. Second, they therefore imply that ignoring the shadow economy leads to mistakes in measured efficiency.

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[9] Those countries are Australia, Austria, Indonesia, Iran, Jordan, the Netherlands, New Zealand, Singapore, Switzerland, and the United Kingdom.

[10] These countries are Bolivia, Brazil, Honduras, Mexico, Nigeria, Panama, Peru, Philippines, Thailand, Turkey, Venezuela, and Zimbabwe.

Finally, our results provide guidance to the empirical literature on economic output and productivity at large. Given that official output figures overlook a sizeable share of total activity, future research on the determinants and effects of a country's production should clearly start by a reflection on which definition of output, official or total, is relevant to the question at hand. Our results suggest that the answer to this question need not always be official output.

References

Adkins, C., R. Moomaw, and A. Savvides. (2002) Institutions, freedom, and technical efficiency, *Southern Economic Journal*, 69, 92-108.

Bajada, C., and F. Schneider (2005) The shadow economies of the Asia-Pacific, *Pacific Economic Review*, 10, 379-401.

Breusch, T. (2005a) The Canadian Underground Economy: An Examination of Giles and Tedds, *Canadian Tax Journal*, 53, 367-391.

Breusch, T. (2005b) Estimating the Underground Economy, Using MIMIC Models, Working Paper, National University of Australia, Canberra, Australia

Caselli, F., (2005) Accounting for cross-country income differences, in *Handbook of economic growth* (Eds.) P. Aghion and S. Durlauf, Elsevier, 679-742.

Chatterjee, S., K. Chaudhuri, and F. Schneider (2003) The Size and Development of the Indian Shadow Economy and a Comparison with other 18 Asian Countries: An Empirical Investigation, Economics working papers 2003-02, Department of Economics, Johannes Kepler University Linz.

Collins, S.M., B. P. Bosworth, and D. Rodrik. (1996) Economic growth in East Asia: Accumulation versus assimilation, *Brookings Papers on Economic Activity*, 2, 135-203.

Del'Anno, R. and F. Schneider. (2003) The shadow economy of Italy and other OECD countries: What do we know?, *Journal of Public Finance and Public Choice*, 21, 97-120.

Del'Anno, R. (2003) Estimating the shadow economy in Italy: A structural equation approach, Discussion Paper, Department of Economics and Statistics, University of Salerno.

Friedman, E., S. Johnson, D. Kaufmann and P. Zoido-Lobatón (2000) Dodging the grabbing hand: the determinants of unofficial activity in 69 countries, *Journal of Public Economics*, 76, 459-493, 2000.

Giles, D.E.A. (1997a) Causality between the measured and underground economies in New Zealand, *Applied Economic Letters*, 4, 63-67.

Giles, D.E.A. (1997b) Testing the asymmetry in the measured and underground business cycles in New Zealand, *Economic Record*, 71, 225-232.

Giles, D.E.A. (1999a) Measuring the hidden economy: Implications for econometric modelling, *Economic Journal*, 109, 370-380.

Giles, D.E.A. (1999b) Modelling the hidden economy in the tax-gap in New Zealand, *Empirical Economics*, 24, 621-640.

Giles, D.E.A. (1999c) The rise and fall of the New Zealand underground economy: are the reasons symmetric?, *Applied Economic Letters*, 6, 185-189.

Giles, D.E.A. and LM. Tedds (2002) Taxes and the Canadian Underground Economy, Canadian Tax Paper No. 106, Canadian Tax Foundation, Toronto/Ontario.

Giles, D.E.A., Tedds, L.M., and Werkneh, G. (2002) The Canadian underground and measured economies, *Applied Economics*, 34, 2347-2352.

Hall R. and C.I. Jones (1999) Why do some countries produce so much more output per worker than others?, *Quarterly Journal of Economics*, 114, 83-116.

International Labor Office (1972) *Employment, income and equality: A strategy for increasing productivity in Kenya*, ILO.

Johnson, S., Kaufmann, D., and P. Zoido-Lobaton (1998a) Regulatory burden and the unofficial economy, *American Economic Review*, 88, 387-392.

Johnson, S., Kaufmann, D., and P. Zoido-Lobatón (1998b) Corruption, public finances and the unofficial economy. Washington, D.C.: The World Bank, discussion paper.

King, R.G. et R. Levine (1994) "Capital fundamentalism, economic development, and economic growth", *Carnegie-Rochester Conference Series on Public Policy*,40, 259-292.

Klenow P. and A. Rodriguez-Clare (1997) The neoclassical revival in growth economics: Has it gone too far?, in *NBER Macroeconomics Annual 1997* (Eds.) B.S. Bernanke and J.J. Rotemberg, MIT Press.

Kneller, R., and P.A. Stevens (2003) The specification of the aggregate production function in the presence of inefficiency, *Economics Letters*, 81, 223-226.

Livingstone, I. (1991) A reassessment of Kenya's rural and urban informal sector, *World*

Development, 19, 651-670.

Méon P.-G. and L. Weill (2004) Does Corruption Hamper Efficiency? A Frontier Analysis, *Empirical Economics Letters*, 3, 21-28.

Méon P.-G. and L. Weill (2005) Does better governance foster efficiency? An aggregate frontier analysis, *Economics of Governance*, 6, 75-90.

Pozo, Susan (ed.) (1996) Exploring the Underground Economy: Studies of Illegal and Unreported Activity, Michigan: W.E. Upjohn, Institute for Employment Research.

Prescott E.C. (1998) Needed: A theory of total factor productivity, *International Economic Review*, 39, 525-551.

Schneider, F. (1994) Measuring the size and development of the shadow economy. Can the causes be found and the obstacles be overcome? in *Essays on Economic Psychology* (Eds.) Brandstaetter, Hermann, and Güth, Werner, Berlin, Heidelberg, Springer Publishing Company, 193-212.

Schneider, F. (1997) The shadow economies of Western Europe, *Journal of the Institute of Economic Affairs*, 17, 42-48.

Schneider, F. (2003) The shadow economy, in *Encyclopedia of Public Choice* (Eds.) C.K. Rowley and F. Schneider , Kluwer Academic Publishers, Dordrecht.

Schneider, F. (2005) Shadow economies around the world: What do we really know?, *European Journal of Political Economy*, 21, 598-642.

Schneider, F. (2006) Shadow Economies of 145 countries all over the world: What do we know?, Discussion paper, Department of Economics, University of Linz, Linz, Austria.

Schneider, F., and D.H. Enste (2000) Shadow economies: size, causes, and consequences, *Journal of Economic Literature*, 38, 77-114.

Tanzi, V. (1999) Uses and abuses of estimates of the underground economy, *Economic Journal*, 109, 338-340.

Thomas, J.J. (1992) *Informal Economic Activity*, LSE, Handbooks in Economics, London: Harvester Wheatsheaf.

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Appendix:

Sample of countries:

Algeria, Angola, Argentina, Australia, Austria, Bangladesh, Belgium, Benin, Bolivia, Botswana, Burkina Faso, Burundi, Brazil, Cameroon, Canada, Central African Republic, Chad, Chile, China, Colombia, Congo (Republic),Costa Rica, Côte d'Ivoire, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Ethiopia, Fiji, Finland, France, Ghana, Greece, Guatemala, Guinea, Haiti, Honduras, Hong Kong, India, Indonesia, Iran, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kenya, Korea (Republic), Lesotho, Madagascar, Malawi, Malaysia, Mali, Mexico, Morocco, Mozambique, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Portugal, Romania, Rwanda, Senegal, Sierra Leone, Singapore, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Syria, Taiwan, Tanzania, Thailand, Togo, Tunisia, Turkey, Uganda, United Kingdom, USA, Uruguay, Venezuela, Zaire, Zambia, Zimbabwe.