“DOES TAKING THE SHADOW ECONOMY INTO ACCOUNT MATTER TO MEASURE AGGREGATE EFFICIENCY?”

Pierre-Guillaume Méon, Friedrich Schneider, Laurent Weill.
Does taking the shadow economy into account matter to measure aggregate efficiency?

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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.

Keywords: shadow economy, income, aggregate productivity, efficiency.

JEL Classification: O11, O17, O47, O5.

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. (1998) or Schneider and Feine (2000). In particular, assessments of productivity at the aggregate
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. 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. Then, the efficiency score is computed by comparing the optimal output per worker with the effective output per worker.
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 only consider the most common production functions analyzed in the literature, the Cobb-Douglas and the translog functions. Those specifications respectively read:

\[
\ln(Y_i) = \beta_0 + \beta_1 \ln(K_i) + \beta_2 \ln(L_i) + v_i - u_i
\]

\[
\ln(Y_i) = \beta_0 + \beta_1 \ln(K_i) + \beta_2 \ln(L_i) + \beta_3 \ln(K_i)^2 + \beta_4 \ln(L_i)^2 + \beta_5 \ln(K_i) \ln(L_i) + v_i - u_i
\]

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 \( \sigma_v^2 \). \( u_i \) is the inefficiency term. It is a one-sided component with variance \( \sigma_u^2 \). 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.

### 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:

\[
K_t = (1 - \delta)K_{t-1} + I_t
\]

Where \( I_t \) is investment and \( \delta \) is the depreciation rate, which is assumed to be equal to 0.06. 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.\(^1\)

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.

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\(^1\) 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.
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 DYMIMIC (dynamic multiple-indicators multiple-causes) and currency demand estimation technique.²

Figure 2: Development of the shadow economy over time.

The DYMIMIC 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 DYMIMIC model here consists of two parts. The measurement model links the unobserved variables to observed indicators.³ 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 size of the shadow economy is assumed to be influenced by a set of indicators, thus capturing the structural dependence of the shadow economy on variables that may be useful in predicting its movement and size in the future. The interaction over time between the causes $Z_{it} (i = 1, 2, \ldots, k)$, the size of the shadow economy $X_t$ in time $t$,

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² A critical survey of existing methods to estimate the shadow economy can be found in Schneider (2006).
³ One of the latest paper dealing extensively with the DYMIMIC approach, its development and its weaknesses is from Del’Anno (2003) and the excellent study by Giles and Tedds (2002), as well as Breusch (2005a, 2005b).
and the indicators $Y_t(j = 1, 2, \ldots, p)$ is shown in Figure 2.

There is a large body of literature on the possible causes and indicators of the shadow economy. 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 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, Tedds and Werkneh (2002), Giles and Tedds (2002), Chatterjee, Chaudhury and Schneider (2006) 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.

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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.

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. The sample includes both developed and developing countries. Summary statistics are presented in table 1 above.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Definition</th>
<th>Mean</th>
<th>S.D.</th>
</tr>
</thead>
<tbody>
<tr>
<td>$Y$</td>
<td>Official output (billions of US$)</td>
<td>331.93</td>
<td>939.63</td>
</tr>
<tr>
<td>$K$</td>
<td>Capital stock (billions of US$)</td>
<td>721.77</td>
<td>2136.38</td>
</tr>
<tr>
<td>$L$</td>
<td>Number of workers (millions)</td>
<td>23349428.26</td>
<td>13.73</td>
</tr>
<tr>
<td>$H$</td>
<td>Average years of schooling</td>
<td>5.74</td>
<td>2.96</td>
</tr>
<tr>
<td>$S$</td>
<td>Shadow economy (percentage of $Y$)</td>
<td>33.65</td>
<td>8.60</td>
</tr>
</tbody>
</table>

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 $Y_t^* = (1 + S_t)Y_t$, where $S_t$ is the ratio of unofficial to official output.

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 whose results are displayed in table 2.

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Official output (1a)</td>
<td>Corrected output (1b)</td>
</tr>
<tr>
<td>$\beta_0$</td>
<td>2.874</td>
<td>3.702</td>
</tr>
<tr>
<td></td>
<td>(6.93)</td>
<td>(8.72)</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>0.694</td>
<td>0.657</td>
</tr>
<tr>
<td></td>
<td>(34.44)</td>
<td>(32.82)</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>0.299</td>
<td>0.323</td>
</tr>
<tr>
<td></td>
<td>(10.24)</td>
<td>(11.13)</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>0.132</td>
<td>0.119</td>
</tr>
<tr>
<td></td>
<td>(3.42)</td>
<td>(3.05)</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.622</td>
<td>0.536</td>
</tr>
<tr>
<td></td>
<td>(2.86)</td>
<td>(1.88)</td>
</tr>
<tr>
<td>log-likelihood</td>
<td>−14.39</td>
<td>−13.78</td>
</tr>
<tr>
<td>$N$</td>
<td>97</td>
<td>97</td>
</tr>
</tbody>
</table>

Absolute $t$-statistics in parentheses. The sigma statistics is defined as $\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$. The gamma statistics is defined as $\gamma = \sigma_v^2 / (\sigma_u^2 + \sigma_v^2)$. Coefficients significant at least at the ten percent level are in bold.
Table 2b: Stochastic frontier results: Translog

<table>
<thead>
<tr>
<th></th>
<th>Model 3</th>
<th></th>
<th>Model 4</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Official output (3a)</td>
<td>Corrected output (3b)</td>
<td>Official output (4a)</td>
<td>Corrected output (4b)</td>
</tr>
<tr>
<td>$\beta_0$</td>
<td>2.266</td>
<td>0.322</td>
<td>6.112</td>
<td>5.398</td>
</tr>
<tr>
<td></td>
<td>(0.54)</td>
<td>(0.08)</td>
<td>(1.44)</td>
<td>(1.20)</td>
</tr>
<tr>
<td>$\beta_1$</td>
<td>0.511</td>
<td>0.720</td>
<td>0.161</td>
<td>0.286</td>
</tr>
<tr>
<td></td>
<td>(1.55)</td>
<td>(2.16)</td>
<td>(0.37)</td>
<td>(0.62)</td>
</tr>
<tr>
<td>$\beta_2$</td>
<td>0.664</td>
<td>0.645</td>
<td>0.769</td>
<td>0.727</td>
</tr>
<tr>
<td></td>
<td>(1.94)</td>
<td>(1.88)</td>
<td>(1.73)</td>
<td>(1.53)</td>
</tr>
<tr>
<td>$\beta_3$</td>
<td>0.012</td>
<td>-0.002</td>
<td>0.001</td>
<td>-0.016</td>
</tr>
<tr>
<td></td>
<td>(1.06)</td>
<td>(0.18)</td>
<td>(0.05)</td>
<td>(0.67)</td>
</tr>
<tr>
<td>$\beta_4$</td>
<td>0.008</td>
<td>-0.012</td>
<td>-0.024</td>
<td>-0.051</td>
</tr>
<tr>
<td></td>
<td>(0.40)</td>
<td>(0.56)</td>
<td>(0.64)</td>
<td>(1.28)</td>
</tr>
<tr>
<td>$\beta_5$</td>
<td>-0.025</td>
<td>0.002</td>
<td>0.019</td>
<td>0.058</td>
</tr>
<tr>
<td></td>
<td>(0.95)</td>
<td>(0.09)</td>
<td>(0.36)</td>
<td>(1.03)</td>
</tr>
<tr>
<td>$\sigma$</td>
<td>0.132</td>
<td>0.118</td>
<td>0.194</td>
<td>0.169</td>
</tr>
<tr>
<td></td>
<td>(3.53)</td>
<td>(3.10)</td>
<td>(3.54)</td>
<td>(3.20)</td>
</tr>
<tr>
<td>$\gamma$</td>
<td>0.640</td>
<td>0.543</td>
<td>0.838</td>
<td>0.711</td>
</tr>
<tr>
<td></td>
<td>(3.15)</td>
<td>(1.95)</td>
<td>(6.46)</td>
<td>(3.56)</td>
</tr>
<tr>
<td>$\log$-likelihood</td>
<td>-13.55</td>
<td>-13.16</td>
<td>-16.89</td>
<td>-18.93</td>
</tr>
<tr>
<td>$LL$ ratio</td>
<td>1.68</td>
<td>1.24</td>
<td>1.16</td>
<td>1.86</td>
</tr>
<tr>
<td>$N$</td>
<td>97</td>
<td>97</td>
<td>87</td>
<td>87</td>
</tr>
</tbody>
</table>

Absolute t-statistics in parentheses. The sigma statistics is defined as $\sigma = (\sigma_u^2 + \sigma_v^2)^{1/2}$. The gamma statistics is defined as $\gamma = \sigma_v^2 / (\sigma_u^2 + \sigma_v^2)$. Coefficients significant at least at the ten percent level are in bold.

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.

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 efficiency scores with uncorrected efficiency scores: Cobb-Douglas

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Official output (1a)</td>
<td>Corrected output (1b)</td>
</tr>
<tr>
<td>Min.</td>
<td>0.444</td>
<td>0.539</td>
</tr>
<tr>
<td>Max.</td>
<td>0.934</td>
<td>0.937</td>
</tr>
<tr>
<td>Mean</td>
<td>0.808</td>
<td>0.828</td>
</tr>
<tr>
<td>Median</td>
<td>0.826</td>
<td>0.835</td>
</tr>
<tr>
<td>Std. dev.</td>
<td>0.0802</td>
<td>0.0655</td>
</tr>
<tr>
<td>Pearson</td>
<td>-</td>
<td>0.964</td>
</tr>
<tr>
<td>Spearman</td>
<td>-</td>
<td>0.945</td>
</tr>
</tbody>
</table>

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 table 3 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.

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.

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.

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<tr>
<td><strong>2005</strong></td>
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<td>N° 05-10.RS</td>
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</tr>
</tbody>
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