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Waste Not, Want Not: The Efficiency of Health Expenditure in Emerging and Developing Economies

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Waste Not, Want Not: The Efficiency of Health Expenditure in Emerging and Developing Economies

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Abstract

Public health spending is low in emerging and developing economies relative to advanced economies and health outputs and outcomes need to be substantially improved. Simply increasing public expenditure in the health sector, however, may not significantly affect health outcomes if the efficiency of this spending is low. This paper quantifies the inefficiency of public health expenditure and the associated potential gains for emerging and developing economies using a stochastic frontier model that controls for the socioeconomic determinants of health, and provides country-specific estimates. The results suggest that African economies have the lowest efficiency. At current spending levels, they could boost life expectancy up to about five years if they followed best practices.

JEL Classification Numbers: H51, I12, I18

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Contents Page

I. INTRODUCTION

> "There has been much discussion of how to cut government spending, but too little attention has been devoted to how to make government spending more effective. And yet, without more creative approaches to providing government services, their cost will continue to rise inexorably over time. ….Politicians can and will promise to do a better job, but they cannot succeed unless we identify ways to boost government services' efficiency and productivity." Kenneth Rogoff, "The Unstarvable Beast," *Project Syndicate*, January 2, 2013.

Improving the efficiency of public spending on health care is a priority across the globe. Previous research indicates significant inefficiencies in this spending in advanced economies, as well as in emerging and developing ones (Herrera and Pang, 2005; Gupta and others, 2007; Verhoeven, Gunnarsson, and Carcillo, 2007; Afonso, Schuknecht, and Tanzi, 2010; and Joumard, André, and Nicq, 2010). Despite lower levels of spending for emerging and developing economies, such inefficiency (measured in terms of outputs relative to inputs) leads to a considerable waste of resources (Grigoli and Ley, 2012), and reducing such waste can help to boost the much-needed improvement in health indicators.

The conclusions from previous research need to be interpreted with caution, however, given the drawbacks of the methodologies they employed. Most of the papers measuring the efficiency of health spending in emerging and developing economies use non-parametric techniques that did not control for the diverse set of factors that influence health outputs/outcomes. These factors include educational attainment; urbanization (which eases the access to health care); private levels of health spending; lifestyle behaviors (such as alcohol consumption); environmental factors (such as access to sanitation facilities and clean water); and contagious disease indicators (tuberculosis and HIV diffusion). If these factors are not incorporated in the analysis, then rankings based on the relationship between public health spending and outcomes alone can be misleading.

In this paper, we attempt to measure public expenditure inefficiency in the health sector for a sample of 80 emerging and developing economies over the 2001–10 period. We depart from most of the existing literature that uses non-parametric techniques and provide updated estimates of efficiency scores derived from a stochastic frontier model that controls for several socioeconomic determinants of heath sector performance. We also rigorously test for the robustness of our results under different model specifications, lag structures, and assumptions regarding the distribution of the error term used in estimating the stochastic frontier model.

Our findings suggest that African economies have the lowest efficiency, whereas the top positions in the efficiency ranking are dominated by Western Hemisphere and Asian economies. The efficiency scores imply that, on average and at current spending levels, the bottom quartile of the sample could increase life expectancy up to almost five years. This contrasts sharply with our finding that an increase of 10 percent in public health spending would only increase life expectancy in these economies by two months.

This paper is structured as follows. Section II reviews the literature, with a focus on the techniques used for the analysis of the efficiency of education and health spending in emerging and developing economies. Section III presents some stylized facts, and discusses the empirical strategy of our analysis and its results. Section IV concludes the paper.

II. Measuring the Efficiency of Health Expenditure: A Selective Literature Review

In recent years, the literature analyzing the efficiency of public expenditure has expanded considerably but there are only a few contributions on emerging and developing economies. Most studies have focused on advanced economies, reflecting the greater availability of data on both inputs and outputs/outcomes.[2] We provide here an overview of some recent papers on emerging and developing economies, with special attention to the methodologies applied. In particular, we split the review between those papers that adopted non-parametric techniques—such as Free Disposal Hull (FDH) and Data Envelopment Analysis (DEA)—and those that adopted parametric techniques—such as the stochastic frontier analysis (SFA). Within each group, we report the conclusions in chronological order.

A. Non-Parametric Methods

One of the first studies on emerging and developing economies is by Gupta and Verhoeven (2001). The authors measure health and education spending efficiency for a sample of 85 countries during 1984–95, using a non-parametric technique. For health, per capita public expenditure (measured in PPP terms) is used as input indicator. Life expectancy, infant mortality, and DPT immunizations are selected as output indicators. Before performing the efficiency analysis, the authors employed regression analysis to assess whether government spending affected health outcomes. They also note that GDP per capita is highly collinear with health expenditure and that this affects the statistical significance of the latter on health outcomes. While the authors acknowledge that there can be lags between spending and its effect on outcomes, they do not address the problem because of the high autocorrelation of the expenditure time series. The authors employ the FDH technique and estimate the efficiency of government expenditure by running different combinations of the one-input, one-output models. To control for the impact of the level of economic development and health outcomes, the sample is divided into low- and high-income countries. They conclude that African economies are inefficient in providing health services

[2]Health care outputs are mainly measured by the number of medical treatments (e.g., number of surgical procedures, doctor consultations, immunizations, and others). Ultimately, these outputs lead to outcomes or gains in the population's health status (e.g., life expectancy, mortality rates, and others).

relative to their Asian and Western Hemisphere peers. They also find that, on average, the level of inefficiency is positively correlated with the level of government expenditure. Gupta and others (2007) adopt another popular non-parametric technique, DEA, to assess the efficiency of health and education spending for a sample of 50 low-income countries. The inputs for the model are per capita health expenditure in PPP dollars, while the outcomes are indicators that are used to monitor progress toward the Millennium Development Goals (infant mortality, child mortality, and maternal mortality). The results suggest that countries with the lowest income per capita have the lowest efficiency scores and that there is significant room for increasing spending efficiency. A correlation analysis between the efficiency scores and other variables is performed, along with multivariate truncated regression analysis. The authors argue that countries with better governance and fiscal institutions, better outcomes in the education sector, and lower prevalence of HIV/AIDS tend to achieve greater efficiency in health spending.

Herrera and Pang (2005) employ both FDH and DEA to estimate public expenditure efficiency in the health and education sectors for a sample of 140 developing countries during 1996–2002. For health, the authors take four output and outcome indicators (life expectancy, disability adjusted life expectancy (DALE), and DPT and measles immunizations). However, as an input indicator, they depart from the previous literature by employing the orthogonal component of the sector’s public expenditure to GDP. The orthogonal component is estimated as the residual from a regression of public expenditure to GDP. This is thought to tackle the problems caused by the correlation between social spending and level of economic development. In the second part of the paper, the authors develop an econometric model to explain the variation in inefficiency across countries. They find that inefficiency tends to be associated with high expenditure levels, high wage bills, high public provision of services, high income inequality, and the prevalence of HIV/AIDS.

B. Parametric Methods

The literature on health spending efficiency using parametric methods starts with Evans and others (2000). The authors perform an analysis on a panel dataset of 191 countries (including advanced economies) for the 1993–97 period by using a fixed-effects panel data estimator and corrected ordinary least squares (COLS).[3] Two dependent variables are employed: DALE and a composite index of DALE including dispersion of the child survival rate, responsiveness of the health care system, inequities in responsiveness, and fairness of financial contribution. The input variables are health expenditure and years of schooling, with the addition of country fixed effects. The authors propose a ranking of countries and check its robustness by changing the functional form of the translog regressions. They argue

[3]The COLS procedure consists of two steps. In the first step, OLS is used to obtain consistent and unbiased estimates of the slope parameters and a consistent but biased estimate of the intercept. In the second step, the estimated intercept is shifted up by the maximum value of the OLS residuals.

that income per capita should not directly affect health outcomes, but rather should impact the ability to purchase better care or better education, which are proxied by the other independent variables. To control for the effect of other components of income per capita, they compute the orthogonal component of health expenditure and years of schooling to GDP per capita and add it as a regressor. They find the results are robust to these different model specifications.

The study by Evans and others has been criticized on several grounds. Greene (2004 and 2005a) argues that with a sample as diverse as the one used in the study, the inclusion of fixed effects can pick up unmeasured cross-country heterogeneity as well as any inefficiency in the provision of health care services. If this is the case, the estimated scores and rankings of countries with respect to the efficiency of spending could be biased. He also notes that the weighting used to compose the index could influence the results. Anand and others (2003) point out that the study does not incorporate the lag between health spending and outcomes. While Murray and Evans (2003) address some of the critiques, Anand and others (2003) argue that additional work is needed to deal with these issues.

Following the strand of literature initiated by Evans and others (2000), Jayasuriya and Wodon (2003) use SFA to estimate health and education efficiency frontiers for a sample of 76 countries for the period 1990–98. For health, the authors take life expectancy as an output variable; and real GDP per capita, adult illiteracy, and health expenditure per capita (private and public) as input variables. In a second step, they analyze the determinants of the estimated efficiency scores using regression analysis. The models include governance indicators and urbanization as explanatory variables (both in levels and squared) to capture possible nonlinearities. The findings suggest that urbanization and bureaucratic quality are strongly and significantly associated with efficiency, while the evidence is not conclusive for the corruption variable.

Greene (2005b) updates the 2005 study by Herrera and Pang using SFA. For health, he employs life expectancy, DALE, DPT and measles immunizations as dependent variables; and private and public health spending as explanatory variables. He also includes aid, the literacy rate, and an HIV/AIDS dummy. The author concludes that, beyond public health spending, the literacy rate positively contributes to health outcomes, while HIV/AIDS exerts a negative impact.

III. How Efficient Is Health Spending in Emerging and Developing Economies?

A. Stylized Facts

Emerging and developing economies are very different from advanced ones in terms of health system performance, socioeconomic conditions, and quality of governance.[4] Table 1 presents the country group averages for some selected indicators over the decade 2001–10. Public spending on health averages 3.2 percent of GDP in emerging and developing economies, about half that of advanced economies. The differences are even more pronounced when measured in terms of spending per capita, where outlays in advanced economies are eight times the amount in the emerging and developing world.

In terms of health outputs and outcomes, emerging and developing economies score systematically worse than advanced ones. A child is expected to live about 15 years longer in an average advanced economy than in an emerging and developing one. Even more striking are the figures for mortality rates. For example, the mortality rate for children under age 5 in emerging and developing economies is eleven times the rate in advanced economies. Differences in immunization rates, however, are less extreme, reflecting humanitarian organizations' efforts in providing vaccines in less developed economies.

Unsurprisingly, the economic and social indicators that have a bearing on health outcomes are less favorable in emerging and developing economies. Extreme poverty is more widespread, income per capita is lower, and income inequality (as measured by the Gini coefficient) is higher. Educational attainment is also markedly lower in emerging and developing economies, as is the quality of governance. The consumption of alcohol, however, is higher in advanced economies. Diseases such as tuberculosis and HIV are significantly more prevalent in emerging and developing economies and access to sanitation facilities and clean water is more difficult.

[4]The IMF country classification is adopted here (for more details see http://www.imf.org/external/pubs/ft/weo/2013/01/weodata/weoselagr.aspx).

Table 1. Selected Health and Social Indicators
(Averages 2001–10)

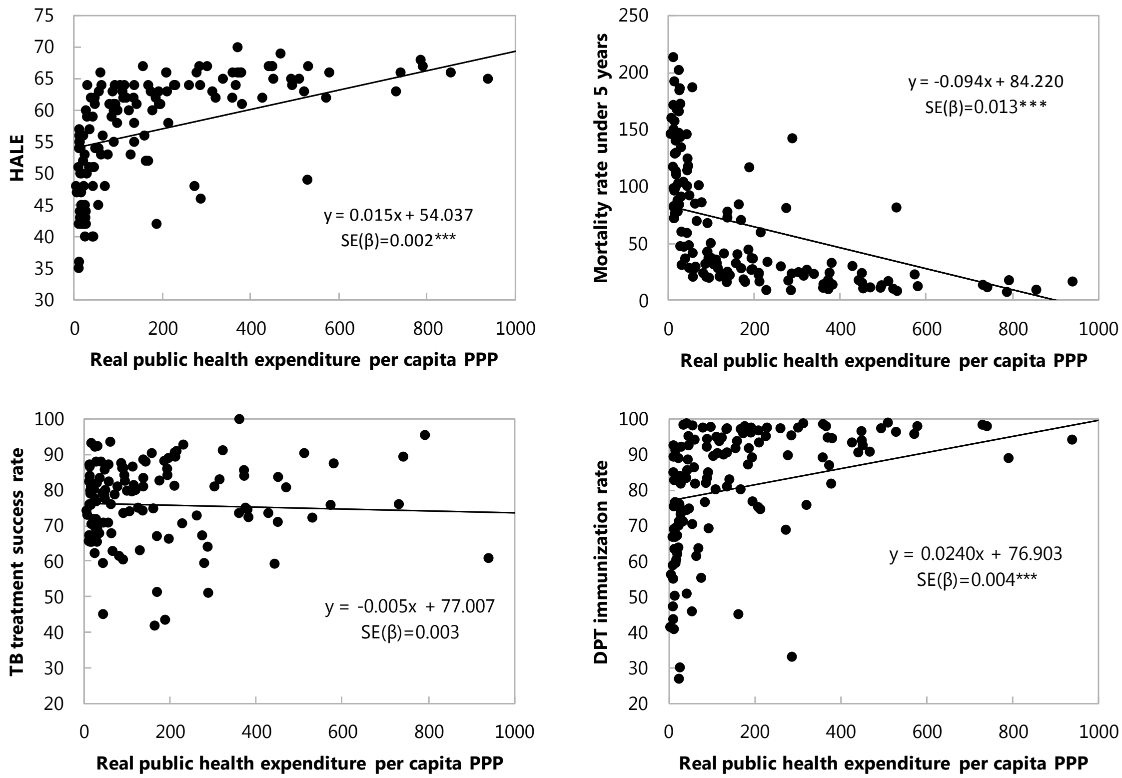
	Advanced	Emerging and Developing
Health expenditure		
Real public expenditure per capita (PPP, int. dollars)	1,731	221
Real private expenditure per capita (PPP, int. dollars)	768	159
Public expenditure (in percent of GDP)	6.0	3.2
Private expenditure (in percent of GDP)	2.4	2.7
Health ouputs/outcomes		
HALE (in years at birth)	72.2	57.2
Life expectancy (in years at birth)	79.1	65.1
Mortality rate under 5 years (per 1,000 live births)	5.2	59.5
Infant mortality rate (per 1,000 live births)	3.9	38.4
Maternal mortality rate (per 100,000 live births)	9.1	269.3
TB treatment success rate (in percent of cases)	74.7	77.7
DPT immunization rate (in percent)	94.5	84.0
Measles immunization rate (in percent)	91.8	83.2
Polio immunization rate (in percent)	94.3	84.8
Economic and social indicators		
Real GDP per capita (PPP, int. dollars)	31,086	7,485
Poverty (below int. dollars 2 per day, percent of population)	0.8	27.2
Years of schooling (in percent of population over 25)	10.8	6.7
Population density (per square km of land area)	379.3	117.3
Gini coefficient	0.30	0.43
Alcohol consumption (in liters per capita among adults)	9.7	4.3
Sanitation facilities (in percent of population with access)	99.7	63.8
TB diffusion (per 100,000 people)	14.6	169.1
HIV diffusion (in percent of 15-49 years population)	0.2	2.6
Adult literacy rate (in percent of population over 15)	97.3	79.8
Water source (in percent of population with access)	99.8	81.9
Governance indicators		
WGI political stability (-2.5 to 2.5)	0.82	-0.31
WGI voice and accountability (-2.5 to 2.5)	1.23	-0.37
WGI government effectiveness (-2.5 to 2.5)	1.51	-0.42
CPIA public sector transparency (1 to 6)	…	2.87
CPIA public administration quality (1 to 6)	…	2.99

Sources: WDI, WGI, and WHO.

Higher public health expenditure is generally associated with better health outputs and outcomes. Nevertheless, there are significant differences across economies, even within the emerging and developing economies group. The scatter plots in Figure 1 show the five-year average of real health expenditure per capita in PPP terms and the averages for health outputs/outcomes over the subsequent five year period. The subsequent (rather than concurrent) time period is used to capture the fact that health spending affects outputs and outcomes with a lag. As expected, the relationship between public health expenditure and health adjusted life expectancy (HALE) [5] is positive and significant, whereas it is negative and significant with mortality rates.[6] Also, immunization rates are positively and significantly correlated with public health expenditure. There is an insignificant relationship, however, between tuberculosis (TB) treatment success and diffusion and public health spending but this may be due to the disease-specific nature of these indicators.[7]

Figure 1. Public Health Expenditure and Outputs/Outcomes

(2001–05 average for public health expenditure and 2006–10 for output/outcome)



Sources: WDI, WGI, and WHO.
Notes: *** p<0.01, ** p<0.05, * p<0.1.
The maximum of the horizontal axis has been set to 1,000 international dollars to ease the visual interpretation of the data. This leaves out Brunei, Palau, Qatar, and UAE.

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[5] HALE estimates the number of healthy years an individual is expected to live at birth by subtracting the years of ill health (weighted according to severity) from overall life expectancy.

[6] As noted by Joumard, André, and Nicq (2010), longevity indicators adjusted for morbidity (or disability) are better indicators of health status than unadjusted figures, but time series are often lacking. Here, the only observation available for HALE over the 2006–10 period is for the year 2007.

[7] The scatter plots for other output/outcome indicators listed in Table 1 are not shown but are available from the authors upon request.

B. Efficiency Measurement

As discussed in Section II, both non-parametric and parametric techniques have been used in the literature to gauge the technical efficiency of public spending.[8] The former approach includes FDH and DEA, whereas the latter comprises a wide family of models generally known as stochastic frontier models, one of which is the SFA.[9] This section provides an overview of the two approaches, present their advantages and disadvantages, and argues that parametric techniques are, under certain conditions, preferable.

Both methods require data on input and output/outcomes but differ in the way they relate the former to the latter. DEA involves an application of linear programming methods where the "best-practice" frontier is built by joining the bundles of units for which no other unit produces the same or more output(s) with a certain amount of input(s). Thus, the DEA frontier is the line that connects those bundles and is convex.[10] FDH is a special case of DEA, where the points connecting the DEA vertices are not included in the frontier. As a result, the FDH frontier is non-convex and connects only the DEA vertices and the free disposal bundles interior to these vertices.[11] The SFA, as any econometric model, requires assumptions regarding the functional form of the production function. Under SFA, a regression is estimated that provides a composite error term. This composite error includes both the idiosyncratic error (due to random variation) and a one-sided disturbance error term. The latter measures the inefficiency of spending.

These two families of methods have advantages and disadvantages. FDH and DEA are extremely sensitive to the presence of outliers, which define the frontier. Moreover, because of their non-parametric nature, they do not address random variation in the data and measurement errors, which becomes part of the inefficiency. SFA, on the other hand, can accommodate randomness and measurement problems and separate them from the measure of inefficiency. However, SFA imposes a certain functional form on the production function and the estimation of this function may prove difficult. A fundamental advantage of SFA, relative to a non-parametric technique, is that it can statistically control for the large number of variables that can influence health outcomes. Non-parametric methods, on the other hand,

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[8]By technical efficiency we refer to the case where public goods and services are provided at the minimum cost. High levels of corruption, for example, may be a cause of low cost effectiveness. We do not assess allocative efficiency, which evaluates whether resources are allocated to the optimal mix of public programs.

[9]For a comprehensive review of methodologies to gauge efficiency, see Ray (2004) for non-parametric methods and Fried, Lovell, and Schmidt (2008) for parametric methods.

[10]In terms of the production function's technology, the DEA frontier implies that linear substitution is possible between observed inputs on an isoquant.

[11]This implies a Leontief-type production function with no substitution of inputs.

have difficulty in handling more than one or two inputs when the sample size is small. When a large number of inputs is used, a high percentage of the observations can be classified as efficient, making it difficult to rank countries in terms of efficiency. To overcome this hurdle, a number of studies using nonparametric techniques perform a "second stage" regression analysis on the inefficiency scores as a way to explain their variation. However, as noted by Burgess (2006), this second step still does not allow one to derive efficiency scores (and a ranking of country efficiency) in a way that incorporates the influence of these factors.

Studies comparing the results of parametric and non-parametric techniques have been inconclusive (see for example Chirikos and Sear, 2000 and Hollingsworth and Wildman, 2003, on health). Nevertheless, there is agreement that non-parametric model results depend on the presence of outliers to create the production frontier and are very sensitive in the case of heterogeneous units (Fiorentino, Karmann, and Koetter, 2006). In this light, it appears that SFA is a better choice for assessing the efficiency of health spending in emerging and developing economies, where levels of income per capita and other determinants of health can vary widely across the sample and should be incorporated into the estimates of efficiency scores.

We estimate the following averaged cross-section stochastic frontier model:

$$y_i = \alpha + \beta' \boldsymbol{x}_i + \delta' \boldsymbol{z}_i + \varepsilon_i$$

$$\varepsilon_i = v_i - u_i$$

$$v_i \sim \mathrm{N}(0, \sigma_v^2)$$

$$u_i \sim \mathrm{F} \tag{1}$$

where y_i represents the log of HALE over the 2006–10 period for the ith economy, x_i is a vector of logs of input variables over 2001–05, z_i is a vector of logs of covariates over 2001–05, and β' and δ' are the vectors of technology parameters. As shown in Table 1, there are several indicators of health output/outcome, but here we opt for HALE as it represents a broad measure of the health status of a country. The term ε_i is a compound error that comprises the normally distributed disturbance v_i, and a one-sided disturbance u_i representing inefficiency. v_i and u_i are assumed to be independent of each other and independently and identically distributed across observations. An assumption about the distribution F of the inefficiency term v_i is needed to estimate the model. Aigner, Lovell, and Schmidt (1977) use a half-normal distribution, Meeusen and van den Broeck (1977) assume an exponential one, Stevenson (1980) opts for the truncated-normal, and Greene (1980a, 1980b, 2003) introduces the Gamma distribution. However, there is no *a priori* reason to prefer a certain distribution. This implies that the best approach could be to assess the sensitivity of the results to different assumptions about the distribution of the error term, as done in this paper.

Beyond the usual set of regressors—such as real public and private expenditure per capita in PPP terms and real GDP per capita in PPP terms—we also include socioeconomic factors. These comprise years of schooling for the population above age 25 (better educated people generally have healthier behaviors); population density per square kilometer of land area (greater population density is associated with greater access to health care); lifestyle characteristics such as alcohol consumption in liters among adults (higher alcohol consumption is generally associated with lower life expectancy); environment factors such as access to sanitation facilities and to clean water; and contagious diseases diffusion indicators for tuberculosis and HIV.[12]

The estimation procedure is based on two sequential steps. In the first step, estimates of the model parameters $\widehat{\theta}$ are obtained by maximizing the log-likelihood function $\ell(\theta)$, where $\theta = (\alpha, \beta', \delta', \sigma_u^2, \sigma_v^2)'$. In the second step, estimates of inefficiency are obtained through the mean of the conditional distribution $f(u_i|\hat{\varepsilon}_i)$, where $\hat{\varepsilon}_i = y_i - \hat{\alpha} - \hat{\beta}' x_i - \hat{\delta}' \boldsymbol{z}_i$.[13]

C. Results

Before performing the SFA estimation, we assess any redundancy in the set of explanatory variables identified before. The multicollinearity diagnostics reported in Table 2 suggest that real GDP per capita in PPP terms should be dropped from the analysis. The variance inflation factor (VIF) for this variable in the preferred specification is high (17.25), above the threshold value of 10. Once the variable is dropped, the reduced model works well, as all the VIFs are lower than 10.

[12]Ravallion (2003) argues that income distribution can affect social indicators because their attainment is mostly determined by the income of the poor. However, the introduction of the Gini coefficient greatly reduces the sample size and prevents the SFA estimation from converging.

[13]Inefficiency estimates can potentially suffer from omitted variable bias, which is common to the research in this area. However, our specification includes many more variables than previous studies and therefore is less susceptible to such bias.

Table 2. Multicollinearity Diagnostics

	Preferred Specification			Reduced Preferred Specification		
	VIF	Tolerance	R-squared	VIF	Tolerance	R-squared
Ln public expenditure pc PPP	12.09	0.083	0.92	4.46	0.224	0.78
Ln private expenditure pc PPP	5.1	0.196	0.80	3.45	0.290	0.71
Ln real GDP PC PPP	17.25	0.058	0.94	…	…	…
Ln years of schooling	2.55	0.392	0.61	2.37	0.422	0.58
Ln population density	1.31	0.762	0.24	1.30	0.768	0.23
Ln alcohol consumption	1.39	0.717	0.28	1.28	0.783	0.22
Ln sanitation facility	3.7	0.270	0.73	3.69	0.271	0.73
Ln water source	3.81	0.262	0.74	3.81	0.262	0.74
Ln TB diffusion	5.03	0.199	0.80	5.02	0.199	0.80
Ln HIV diffusion	1.32	0.231	0.77	4.24	0.236	0.76

Source: Authors' calculations.

Table 3 shows the stochastic frontier regression results, adding one explanatory variable at a time. The first column confirms that public and private expenditure are positively associated with HALE, with the former having a stronger and more significant impact. Columns 2 through 8 show that health outcomes are determined by more than just public and private spending, underscoring the advantage of using SFA for the purpose at hand. Public expenditure is significant in all the specifications but one, and the magnitude of the coefficient is fairly stable at around 0.03. This suggests that a 10 percent increase in public health spending per capita would raise HALE by only two months.[14]

Column 8 presents the results for the preferred specification and assumes a half-normal distribution for the inefficiency term. The results suggest that educational attainment exerts a positive and significant effect on HALE. TB and HIV diffusion are negatively associated with the outcome indicator, as expected. Columns 5 to 7 suggest that access to sanitation facilities positively affects HALE, but this effect becomes insignificant when TB and HIV diffusion are introduced in the specification. Column 9 uses the same specification as in Column 8 but assumes an exponential distribution for the inefficiency term. The estimates are generally robust for public health expenditure, educational attainment and TB and HIV diffusion. Using a truncated- and gamma-distributed inefficiency term was not possible, as the model would not converge under these assumptions.

[14]This calculation is based on an average HALE of 57 years.

Table 3. SFA Regressions

(Five-year average cross-section with five-year lag; dependent variable, in HALE)

	(1) SFA (half-normal)	(2) SFA (half-normal)	(3) SFA (half-normal)	(4) SFA (half-normal)	(5) SFA (half-normal)	(6) SFA (half-normal)	(7) SFA (half-normal)	(8) SFA (half-normal)	(9) SFA (exp.)
Ln public expenditure pc PPP	0.035***	0.020*	0.035***	0.039***	0.022**	0.022*	0.010	0.025**	0.024**
	(0.008)	(0.011)	(0.012)	(0.011)	(0.011)	(0.012)	(0.013)	(0.012)	(0.012)
Ln private expenditure pc PPP	0.033***	0.042***	0.029***	0.034***	0.026**	0.020	0.011	0.016	0.021
	(0.008)	(0.012)	(0.010)	(0.012)	(0.013)	(0.016)	(0.016)	(0.015)	(0.015)
Ln years of schooling		0.076***	0.078***	0.090***	0.070**	0.063**	0.087***	0.053**	0.050**
		(0.021)	(0.024)	(0.030)	(0.030)	(0.032)	(0.031)	(0.025)	(0.024)
Ln population density			0.019***	0.017**	0.014**	0.013	0.011	0.006	0.006
			(0.006)	(0.007)	(0.007)	(0.008)	(0.007)	(0.007)	(0.007)
Ln alchool consumption				-0.019*	-0.014	-0.012	-0.013	-0.009	-0.007
				(0.010)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)
Ln sanitation facility					0.076***	0.076***	0.068***	0.007	0.002
					(0.020)	(0.020)	(0.022)	(0.021)	(0.020)
Ln water source						0.037	0.017	0.072	0.058
						(0.060)	(0.061)	(0.067)	(0.064)
Ln TB diffusion							-0.031***	-0.026**	-0.025**
							(0.011)	(0.011)	(0.010)
Ln HIV diffusion								-0.038***	-0.040***
								(0.007)	(0.006)
Constant	3.860***	3.754***	3.662***	3.619***	3.461***	3.339***	3.657***	3.559***	3.604***
	(0.030)	(0.043)	(0.051)	(0.061)	(0.058)	(0.204)	(0.233)	(0.256)	(0.246)
Observations	145	105	105	93	90	89	89	80	80
R-squared									

Source: Authors' calculations.
Notes: *** p<0.01, ** p<0.05, * p<0.1
Truncated normal and gamma distrubution did not converge.

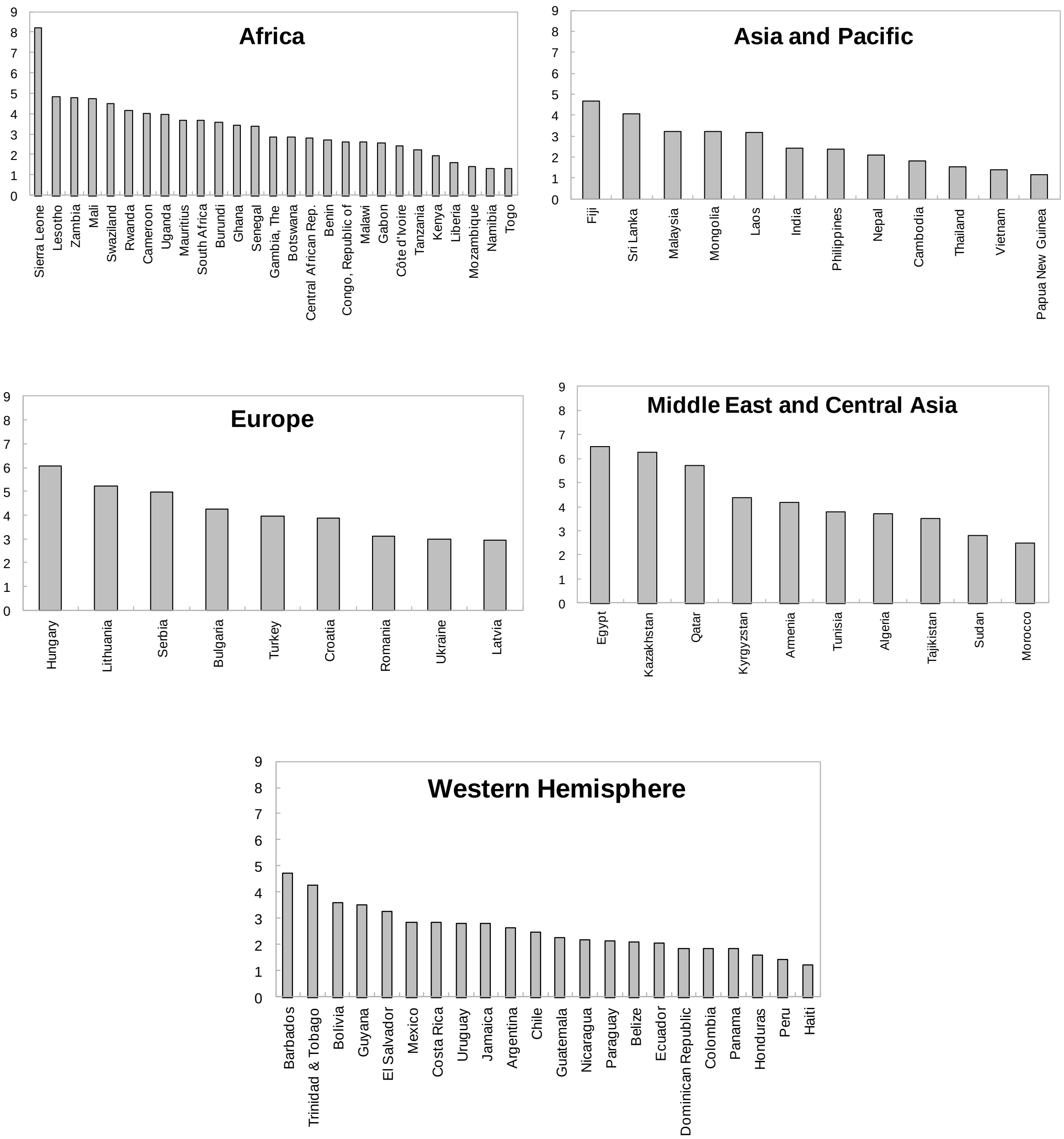
SFA point estimates derived from the specification in Column 8 (our preferred one) are reported in Appendix I. The highest possible score is 1.0, while a score of 0.5, for example, suggests that the level of output (HALE) could be increased by half with the present level of inputs. The higher rankings are dominated by Western Hemisphere and Asian economies, with Papua New Guinea being the most efficient. The results indicate that African economies are the least efficient. Compared to other studies using SFA, the average efficiency score is slightly higher (0.94).[15] This is because our model adds a number of control variables that reduce the size of the error term and result in a better fit for the model.

The efficiency scores derived from the SFA and a DEA with one input (public health expenditure) and one output (HALE) are vastly different and underscore the advantages of an SFA that incorporates the multiple factors that influence health outcomes. In particular, less than half of the economies stay in the same quartile in terms of their ranking on spending efficiency. Furthermore, while 23 percent of the economies in the sample move to the next or the previous quartile, about 10 percent of the economies that are in the most (least) efficient DEA quartile end up in the least (most) efficient one when SFA is used to compute the efficiency scores.

Figure 2 reports the potential gains in life expectancy at current spending levels associated with the efficiency scores of Appendix I. Economies are listed by region and from the most efficient to the least efficient. The results suggest that large potential gains in life expectancy exist in several economies. African economies show large gains reflecting a very low life expectancy at current spending levels, with Sierra Leone being an extreme at 8.2 years and Lesotho, Mali, and Zambia just below four. Western Hemisphere economies, on the other hand, have generally smaller potential gains, reflecting longer life expectancy at current spending levels. If inefficiency were fully removed and current spending levels maintained, Barbados could gain up to 4.7 years, while Haiti only 1.2 years. In Asia and the Pacific the economy with the largest margin is Fiji with 4.7 years, and the economy with the smallest margin is Papua New Guinea with 1.2 years. In the Middle East and Central Asia the extremes are Egypt with 6.5 years and Morocco with 2.5 years. The European sample is composed by only nine economies, with Hungary's potential gains at 6.1 years, and Latvia at three, respectively.

[15] Greene (2004) finds an average efficiency score from 0.81 to 0.85 depending on the specification, and Greene (2005b) from.0.87 and 0.91. Note, however, that the samples used differ from the one of this study.

Figure 2. Potential Gains from Eliminating Inefficiency
(In HALE years)



Source: Authors' calculations.

Another way to assess the importance of improving the efficiency of spending is to compare its effects on HALE with improvements in other determinants of health outcomes. In Table 4 we calculate how much HALE could increase if we raised the performance of countries scoring below the regional mean on public spending, years of schooling, TB diffusion, and spending efficiency. The results indicate that bringing public health expenditure efficiency to the regional average would substantially lengthen HALE across regions. The gains from increasing public spending and reducing TB diffusion are generally the largest. Years of schooling and reductions in HIV diffusion, however, would on average have only modest effects on HALE. Variable-specific effects by country are reported in Appendix II. Since these calculations are based on the SFA coefficients relative to the entire sample, these results must be interpreted with care. They nevertheless provide an idea on how reforms affecting these variables could affect health outcomes.

Table 4. Average Potential Gain from Reaching the Regional Average

(In HALE years)

	Public Exp. Pc PPP	Years of Schooling	TB Diffusion	HIV Diffusion	Efficiency
Africa	1.2	0.1	6.5	0.4	1.5
Asia and Pacific	0.9	0.1	2.4	0.0	1.0
Europe	3.0	0.1	1.0	0.0	0.9
Middle East and Central Asia	4.1	0.1	1.3	0.0	1.3
Western Hemisphere	3.3	0.1	1.9	0.0	0.8

Source: Authors' calculations.
Note: Potential gains from each variable are calculated by multiplying the SFA coefficient by the increase needed to reach the regional average. Above regional average observations are excluded from the potential gain calculations.

To explore further the relationship between public health expenditure and HALE, we report in Table 5 the means by quartile of efficiency, with the first quartile being the most efficient. The results are suggestive of the potential HALE increase that could be achieved if economies produced on the production frontier (that is, eliminated all inefficiency). For the least efficient quartile of countries, for example, 5.1 years of HALE could be gained by moving to the efficiency frontier.

Table 5. Means by Quartile of Technical Efficiency

		Actual			Potential Outcome Increase
	Obs	HALE	Public Expenditure Pc PPP	SFA Efficiency Score	HALE Increase
1st quartile	20	59.2	125.3	0.972	1.7
2nd quartile	20	59.3	185.2	0.956	2.7
3rd quartile	20	56.3	182.6	0.942	3.5
4th quartile	20	52.2	278.4	0.910	5.1

Source: Authors' calculations.

Two important caveats should be mentioned. First, all expenditure efficiency analysis is limited by the availability of data on health outputs and outcomes, and this study is no exception. Increasing life expectancy and reducing mortality rates are not the only objectives of public health spending. Some public health spending may help produce outputs that improve the quality of life but do not affect life expectancy or mortality rates *per se*. Second, like much of the past literature, we measure efficiency relative to economies on the frontier. Having an efficiency score of, say, 0.95 does not mean that the health system can only be made more efficient by 5 percent; it only means that compared to the estimated frontier efficiency can be improved by 5 percent. Hence, efficiency scores would change if the sample were expanded to include other economies that might be highly efficient. Increasing the sample of economies (for example, to include advanced ones), however, would lead to an even more heterogeneous sample and new challenges in estimating the efficiency frontier.[16]

By controlling for exogenous factors that have an effect on health outcomes in the SFA, we generate efficiency scores that are likely to be uncorrelated with the SFA regressors. Thus, any second step analysis with variables included in the first step would not provide a significant coefficient.[17] Nevertheless, the exogenous variables provide insights on how the composition of public health spending can influence health outcomes and, as a consequence, the efficiency of health spending. In particular, the results imply that for any given level of public health spending shifting outlays toward reducing HIV and TB diffusion are associated with higher efficiency. The results also suggest that health outcomes are determined by more than just spending on public health. In particular, a higher educational attainment is associated with higher life expectancy for the same level of spending, suggesting higher efficiency. To assess the effect of variables not captured in our SFA, we also perform a second step analysis with some variables not used in the first step. The results suggest that governance variables (i.e., political stability, voice and accountability, and government effectiveness) do not seem to have a systematic relationship with the efficiency of the health system.

D. Robustness Checks

Robustness checks are undertaken by assessing the correlations between our results for efficiency and the efficiency scores using different dependent variables, different model specifications, and different methodologies. Since our interest is in the ranking of countries, we calculate Spearman and Kendall rank correlation coefficients. The first block of variables from Table 6 indicates the correlations between our ranking and those derived from other SFA specifications, including when we use a health indicator other than HALE. Secondly, some DEA models are run and rankings compared.

It is difficult to state *a priori* how many years it takes for public health expenditure to affect life expectancy. While our results are based on a five-year lag structure, we also run the same

[16] Note that capacity constraints (e.g., an inadequate number of health clinics) may prevent an increase in health spending from translating into better health outcomes at the same rate as in a capacity unconstrained economy.

[17] This is confirmed by the results of correlations between the efficiency scores and independent variables.

model with three- and four-year lags. The rankings are significantly and highly correlated and thus seem robust to different lag structures. Also, the use of expenditure variables in GDP terms instead of per capita PPP terms does not affect the rankings. As shown in Table 3, the results are robust to the use of different assumptions for the inefficiency term. As expected, when substituting the HALE variable with the under-five mortality rate and the infant mortality rate the ranking of countries changes, but the correlation coefficient is surprisingly high and significant.

Some care must be taken in comparing the SFA and DEA results. By definition, DEA cannot address measurement problems and other stochastic influences and does not provide a means to deal with heterogeneity across units of observation. Thus, the comparison between SFA and DEA results is not straightforward, and low correlation coefficients between the efficiency scores using the different methods should be taken as an evidence of the need to control for variables other than public spending. We run DEA models with one input (public health expenditure per capita in PPP terms) and one output (HALE), as well as with a second input (real GDP per capita in PPP terms or the principal component from SFA regressors other than public health expenditure). The Spearman correlation coefficients are statistically significant, and the correlation with our baseline results stays between 46 and 48 percent.

Table 6. Robustness Checks

	Obs	Spearman's Coeff.	Kendall's Coeff.
SFA			
Lag structure			
4 year average for input, 2002–05	64	0.99***	0.99***
3 year average for input, 2003–05	64	0.99***	0.99***
Explanatory variables in percent of GDP	64	0.97***	0.87***
Error term distribution			
Error term exponential	64	0.99***	0.95***
Dependent variable			
Mortality rate under 5 years	64	0.78***	0.58***
Infant mortality rate	64	0.77***	0.57***
DEA			
Input: public health expenditure per capita in PPP terms; output: HALE	64	0.46***	0.33***
Inputs: public health expenditure per capita in PPP terms and real GDP per capita in PPP terms; output: HALE	64	0.48***	0.34***
Inputs: public health expenditure per capita in PPP terms and principal components from SFA regressors other than public health expenditure; output: HALE	64	0.46***	0.32***

Source: Authors' calculations.
Notes: *** p<0.01, ** p<0.05, * p<0.1
The reported correlation coefficients are the ones between the SFA scores derived from the preferred specification and the ones obtained with the change indicated in the relevant line.
Tau-b statistic (adjusted for ties) is reported.

IV. CONCLUSIONS

Emerging and developing economies spend a fraction of the resources allocated to healthcare in advanced economies and have significantly lower health outputs and outcomes. While higher health spending can contribute to better outcomes, so could improvements in the efficiency of this spending. Since health outputs and outcomes are determined by a myriad of socioeconomic and environmental factors, it is important that measures of the efficiency of spending take these into account to the extent allowed by data availability to provide better guidance on the potential scope for efficiency gains.

This paper makes a contribution to this effort by estimating a stochastic frontier model that controls for the socioeconomic and environmental factors that influence health outcomes. The results suggest that on average inefficiency is highest in Africa, while Western Hemisphere and Asian economies are relatively more efficient. There is significant variation, however, in the efficiency of spending within regions, with some economies in Africa, for example, among the most efficient. The efficiency scores reveal that, on average, the last quartile of the efficiency distribution gain up to five years in terms of HALE. By comparison, a 10 percent increase in public health spending per capita would raise HALE by only two months. The results are robust to changes in model specification and assumptions regarding the distribution of the inefficiency term. The use of mortality rates as dependent variables induces some changes but the rank correlations stay between 57 and 78 percent.

From a policy perspective, the results suggest that there can be large gains in health outcomes by improving the efficiency of public health spending. Enhancing the efficiency of spending should thus be a core element of countries' reform strategies. The results also underscore the importance of the composition of health spending to improve its efficiency. In particular, spending aimed at efforts to control TB diffusion should be a priority.

Appendix I. SFA Efficiency Scores

Appendix Table 1. Point Estimates

Country	SFA Efficiency Score	Country	SFA Efficiency Score
Papua New Guinea	0.980	Benin	0.948
Peru	0.979	Sudan	0.946
Vietnam	0.979	Gambia, The	0.946
Haiti	0.978	Croatia	0.946
Thailand	0.976	Tunisia	0.946
Honduras	0.975	Mauritius	0.945
Namibia	0.974	Laos	0.945
Togo	0.974	Botswana	0.944
Panama	0.973	Malawi	0.944
Colombia	0.973	Algeria	0.943
Dominican Republic	0.971	Turkey	0.943
Ecuador	0.969	Bolivia	0.942
Paraguay	0.968	Tajikistan	0.942
Nicaragua	0.967	Sri Lanka	0.940
Cambodia	0.967	Bulgaria	0.940
Mozambique	0.967	Guyana	0.938
Liberia	0.967	Senegal	0.938
Belize	0.966	Central African Rep.	0.937
Chile	0.966	Trinidad and Tobago	0.936
Nepal	0.963	Ghana	0.936
Guatemala	0.963	Armenia	0.936
Philippines	0.963	Barbados	0.934
Argentina	0.962	Fiji	0.930
Morocco	0.961	Serbia	0.929
Kenya	0.961	South Africa	0.929
Costa Rica	0.961	Kyrgyz Republic	0.929
Uruguay	0.960	Lithuania	0.924
Mexico	0.959	Burundi	0.923
India	0.959	Qatar	0.921
Jamaica	0.958	Cameroon	0.918
Latvia	0.956	Hungary	0.916
Romania	0.954	Uganda	0.913
Gabon	0.953	Rwanda	0.911
Malaysia	0.952	Swaziland	0.903
Ukraine	0.952	Egypt	0.902
Tanzania	0.952	Kazakhstan	0.899
Côte d'Ivoire	0.951	Mali	0.898
El Salvador	0.949	Zambia	0.892
Congo, Republic of	0.948	Lesotho	0.892
Mongolia	0.948	Sierra Leone	0.810

Source: Authors' calculations.

Appendix II. Potential Gains from Reaching the Regional Average

Appendix Table 2. Country Estimates

(In HALE years)

Country	Public Exp. Pc PPP	Years of Schooling	TB Diffusion	HIV Diffusion	Efficiency	Total
Africa						
Benin	1.1	0.1	.	.	.	1.2
Botswana	.	.	10.4	0.7	.	11.1
Burundi	1.5	0.1	.	.	0.4	2.1
Cameroon	1.2	.	.	.	0.7	1.9
Central African Rep.	1.6	0.1	.	.	.	1.6
Congo, Republic of	0.8	.	0.5	.	.	1.3
Côte d'Ivoire	1.4	0.0	.	.	.	1.5
Gabon	.	.	.	.	.	0.0
Gambia, The	0.7	0.1	.	.	.	0.8
Ghana	1.1	.	.	.	.	1.1
Kenya	1.3	.	.	.	.	1.3
Lesotho	0.8	.	5.7	0.6	1.8	8.9
Liberia	1.7	0.1	.	.	.	1.8
Malawi	1.2	0.1	0.2	0.2	.	1.6
Mali	1.3	0.2	.	.	1.6	3.0
Mauritius	.	.	.	.	.	0.0
Mozambique	1.2	0.2	3.1	0.1	.	4.7
Namibia	.	.	17.3	0.3	.	17.6
Rwanda	1.2	0.1	.	.	1.0	2.3
Senegal	1.0	0.0	.	.	.	1.0
Sierra Leone	1.6	0.1	1.5	.	5.3	8.4
South Africa	.	.	10.9	0.4	0.2	11.5
Swaziland	.	.	16.4	0.7	1.4	18.5
Tanzania	1.4	.	.	.	.	1.4
Togo	1.6	.	0.1	.	.	1.7
Uganda	1.4	0.0	.	.	0.9	2.3
Zambia	0.8	.	5.7	0.2	1.8	8.5
Asia and Pacific						
Cambodia	1.1	0.0	7.0	0.0	.	8.2
Fiji	.	.	.	.	1.9	1.9
India	1.2	0.1	0.5	.	.	1.8
Laos	1.3	0.1	.	.	0.8	2.2
Malaysia	.	.	.	.	0.4	0.4
Mongolia	.	.	1.0	.	0.7	1.7
Nepal	1.4	0.2	.	0.0	.	1.6
Papua New Guinea	0.1	0.1	2.8	0.0	.	3.0
Philippines	0.8	.	3.0	.	.	3.8
Sri Lanka	0.3	.	.	.	1.3	1.6
Thailand	.	0.0	.	0.0	.	0.1
Vietnam	1.0	0.1	0.3	.	.	1.3
Europe						
Bulgaria	2.4	0.0	.	.	0.0	2.5
Croatia	.	0.0	.	.	.	0.0
Hungary	.	.	.	.	1.8	1.8
Latvia	2.5	.	0.3	0.0	.	2.9
Lithuania	.	.	0.3	.	1.1	1.4
Romania	3.2	.	2.6	.	.	5.8
Serbia	0.5	0.0	.	.	0.8	1.3
Turkey	2.2	0.2	.	.	.	2.4
Ukraine	7.1	.	0.7	0.0	.	7.8
Middle East and Central Asia						
Algeria	1.9	0.0	.	.	.	1.9
Armenia	5.2	.	.	.	.	5.2
Egypt	3.9	0.1	.	.	2.0	6.0
Kazakhstan	2.5	.	2.9	.	2.1	7.5
Kyrgyz Republic	5.5	.	1.4	.	0.2	7.1
Morocco	5.2	0.2	0.0	.	.	5.4
Qatar	.	0.0	.	.	0.8	0.8
Sudan	5.9	0.2	0.4	0.0	.	6.6
Tajikistan	6.0	.	1.6	.	.	7.6
Tunisia	1.3	0.1	.	.	.	1.3
Western Hemisphere						
Argentina	.	.	.	.	.	0.0
Barbados	.	.	.	.	2.0	2.0
Belize	3.1	.	.	0.1	.	3.2
Bolivia	2.9	.	2.5	.	1.2	6.6
Chile	.	.	.	.	.	0.0
Colombia	.	0.0	.	.	.	0.0
Costa Rica	.	.	.	.	0.0	0.0
Dominican Republic	3.5	0.0	0.5	0.0	.	4.1
Ecuador	3.4	0.0	0.6	.	.	4.0
El Salvador	1.5	0.0	.	.	0.8	2.3
Guatemala	4.0	0.2	.	.	.	4.2
Guyana	3.0	.	1.1	0.0	1.3	5.5
Haiti	5.9	0.2	5.2	0.1	.	11.3
Honduras	3.4	0.1	0.8	0.0	.	4.4
Jamaica	2.1	.	.	0.0	0.2	2.3
Mexico	.	.	.	.	0.2	0.2
Nicaragua	3.9	0.1	.	.	.	4.0
Panama	.	.	.	0.0	.	0.0
Paraguay	3.6	0.0	.	.	.	3.7
Peru	2.4	.	2.2	.	.	4.6
Trinidad and Tobago	.	.	.	0.0	1.7	1.7
Uruguay	.	.	.	.	0.1	0.1

Source: Author's calculations.

Note: Potential gains from each variable are calculated by multiplying the SFA coefficient by the increase needed to reach the regional average. Above regional average observations are excluded from the potential gain calculations.

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