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Disentangling the efficiency drivers in country-level global health programs: An empirical study

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ABSTRACT

Motivated by the cost reductions and outcome improvements generated by benchmarking in many industries, we focus on in-country global health programs to identify and quantify opportunities for process improvement. We empirically study the major efficiency drivers of reproductive health (RH) country programs in Sub-Saharan Africa sponsored by international funding organizations. To ensure a level playing field for comparison across countries, we quantify the impact of cross-country heterogeneity and random shocks on the efficiency of RH programs. To analyze these relationships and isolate the effects attributable to managerial inefficiency, we use a three-stage Data Envelopment Analysis (DEA)/Stochastic Frontier Analysis (SFA) model. We show the impact of environmental factors on program efficiency, linking policy making decisions with operational and health outcome performance. We also show that donor fragmentation negatively impacts managerial efficiency, and we suggest actions to mitigate this effect. We then provide a way to improve performance through benchmarking efforts within groups of countries and present an initial prototype of such efforts.

1. Introduction

Resource constraints and the high burden of infectious diseases in many low-income and middle-income countries require domestic government health expenditure to be complemented with overseas financial assistance. This assistance may be in the form of provision of health commodities or other health financing. In 2010, the total donor investments in global health were approximately $28.2 billion.[1] In Sub-Saharan Africa, where the resource constraints are the severest and the disease burden the highest, approximately $8.1 billion was spent on health programs.

Most donors require an assessment of the deployment and performance improvements resulting from their investments. However, the evaluation metrics differ across donor organizations. In recent years, measuring and improving the performance of developing country health programs funded by global monies has become a major concern of funding agencies and policymakers (Glassman et al., 2013). Performance-based financing systems, where future donations are conditioned on predefined results, are used by global health agencies to improve performance (e.g. GAVI[2] and USAID[3]). However such systems are complex and do not always adequately convey incentives for performance improvement (Fan et al., 2013). Common issues impacting the effectiveness of these performance systems are the selection of appropriate performance metrics and the lack of considerations of location-specific factors that can partially affect performance (Eichler and Levine, 2009). Furthermore, a systematic evaluation approach, that is replicable and comprehensible to all stakeholders, is the perfect candidate, as expressed by studies from different funding organizations (Clark et al., 2004; OECD, 2008; Roberts and Khattri, 2012). Additionally, and in the context of donors funding health programs in multiple countries, this evaluation approach needs to be coupled with a benchmarking technique that allows to compare different countries' efficiencies as a source to provide realistic best practices for efficiency improvement and achievement of performance targets.

In this paper, we contribute to the global health supply chain literature by providing a replicable, fair and rigorous approach to

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[1] Source: Institute for Health Metrics and Evaluation, 2013.

[2] http://www.gavi.org/about/governance/gavi-board/minutes/2011/16-nov/minutes/performance-based-funding.

[3] http://pdf.usaid.gov/pdf_docs/pnadw113.pdf.

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measure managerial efficiency of country-level health care programs. We define *managerial efficiency* as the capability of in-country program managers to efficiently run their operations. Using reproductive health (RH) programs as an example, our approach considers both health and supply chain outcomes and allows us to isolate each country's managerial inefficiencies from inefficiencies that are attributable to different countries endowed environmental factors such as logistics infrastructure, location, and public health care status. This enables a fair estimation of managerial efficiencies, where good environmental conditions cannot disguise inefficient program management and bad environmental conditions cannot hide efficient program management. Our study provides an estimate of the impact of changes to these environmental factors to improve overall efficiencies. We also quantitatively analyze the possible influence of donor fragmentation (i.e. number of different funders) on managerial efficiency. The latter impact has barely been tested empirically before.

The modeling approach suggested is a three-stage Data Envelopment Analysis (DEA)/Stochastic Frontier Analysis (SFA) benchmarking methodology to the RH data at a country-level, which is the level at which donors evaluate performance. This technique allows us to analyze efficiency using different sets of variables: input variables, output variables, environmental variables and variables that influence random shocks and managerial inefficiency. Our method quantifies (overall) efficiency obtained in stage 1 and, after recalibrations related to exogenous effects in stage 2, it quantifies *managerial efficiency* in stage 3. Finally, this method allows us to compare each country's performance with other peer countries, and thus determine ways that can help a country achieve relative performance improvement. We do so by describing a methodology to find each country's reference and extended reference set and suggesting a benchmarking process that could help identify specific supply chain and operational best practices. This approach is foreshadowed in a case study based on Botswana and Lesotho. To the best of our knowledge, the current study is the first to employ a DEA/SFA multi-stage technique to evaluate efficiency of global health programs with a commodity/product focus.

2. Literature review

Our modeling approach is based on Data Envelopment Analysis (DEA), which is a nonparametric linear programming method that was initially developed by Farrell (1957) and Charnes et al. (1978). DEA uses linear programming to permit individual Decision Making Units (DMUs) to choose weights associated with inputs and outputs that would maximize their efficiency. In the context of our study, a DMU refers to a country set of all RH programs. In DEA, a country aggregated efficiency is estimated as a non-parametric relationship between the set of outputs and inputs. Applying DEA across all DMUs provides an efficient frontier of performance. This frontier suggests different weighted combinations of inputs and outputs that can enable the maximum possible level of efficiency.

The DEA technique has been employed in many industries, including the health care delivery industry (Hollingsworth, 2008) and at different DMU levels, from hospitals (Cooper et al., 2007; Jacobs, 2001) and nursing homes (Björkgren et al., 2001; Ozcan, 1998) to physicians (Chilingerian, 1995). To our knowledge, our paper is the only one to use DEA techniques to evaluate health care programs performance at the country level. The closest to our work from all DEA studies are some recent papers that assess the efficiency of hospitals in developing countries. For example, Masiye (2007) demonstrated that costs could be lowered by up to 36% without compromising output for a set of Zambian hospitals using DEA.

Regular DEA techniques do not allow to disentangle the effects of endowed environmental factors, random shocks, and managerial efficiency on the overall performance of a DMU, as is the purpose of our paper. The closest method that allows for this is DEA with uncontrollable or non-discretionary variables. However, this method assumes that the direction of influence on efficiency of each one of these variables is known in advance. Other two-stage models have been suggested to avoid to pre-test directions, however random shocks (i.e., luck factor and statistical noise) are not accounted for in any of these methods (Cooper et al., 2007). To account for all these factors, Fried et al. (2002) define a three-stage DEA/SFA framework, where the first stage consist of running DEA with a set of input and output variables. In stage 2 the SFA technique is used to regress the first stage inefficiency slack values decomposing them in three attributable factors: environmental effects, random shocks and managerial inefficiency. Stage 3 consists of running DEA again with adjusted input and/or output values that only account for managerial inefficiencies. This work uses an input-oriented BCC (Banker-Charles-Cooper) as the DEA model of choice and the DMUs are a set of US-hospital affiliated nursing homes. Other papers have proposed refinements of this multi-stage method. For example, Avkiran and Rowlands (2008) suggests a different DEA technique, the non-oriented Slacks-Based Measure (SBM) model, claiming that this type of DEA model is fully unit-invariant and thus more consistent with the use of slacks in the SFA estimates of stage 2. This paper also suggests a different adjustment formula to transition from stage 2 to stage 3 that directly accounts for the impact of environmental factors and statistical noise. Liu and Tone (2008) builds upon these developments to further improve stage 2 by following Battese and Coelli (1995) regression formulation and Greene (2008) specifications in the variance equations of the composed error.

As already mentioned, Stochastic Frontier Analysis (SFA) is another well-known performance evaluation method. Specifically, SFA is a parametric regression-based method for estimating the product efficiency frontier developed by Aigner et al. (1977). This technique requires the specification of functional form to define efficiency and specification of distributional form for the inefficiency term, and it provides random error terms and inefficiency residuals. These error terms allow to account for noise assigning part of the deviations of the frontier to aspects that are not necessarily linked to managerial inefficiencies. SFA has been extensively used in the context of evaluating cross-country health programs. For example, a World Health Organization (WHO) report used SFA to study the national health care system's efficiency of 191 countries using WHO data (WHO, 2000). This report generated discussions between experts in health economics regarding the appropriateness of the methodology. For example Greene (2004) employed the same data to provide a more general SFA study that would distinguish between inefficiency and cross individual heterogeneity, claiming that the later was masqueraded in the initial study. Our method of choice, the three stage DEA/SFA technique, takes advantage of the benefits of SFA that account for these random shocks and environmental effects and the DEA benefits that allow the creation of reference sets to benchmark across different DMUs.

Other techniques besides DEA, SFA or muti-stage DEA-SFA have been used to evaluate performance of health programs. These techniques can be grouped in cost analysis methods (e.g., cost-effectiveness, cost-utility, cost-benefit analysis) and tend to be more direct methods and thus easier to comprehend (Drummond, 2005; Johannesson, 1996). However, they cannot provide a quantitative impact analysis of random shocks, environmental variables or funding concentration as we are obtaining in our work. One example of a practical cost analysis study across countries has been run by the President's Emergency Plan for AIDS Relief (PEPFAR) that attempts to assess the performance of their programs by using facility expenditure tracking to identify outliers (Sangrujee, 2012).

These outliers are explained by acceptable non-quantifiable reasons such as location, population, or infrastructure costs or because of performance gaps.

3. Discussion on major efficiency drivers of global health programs

In this section we discuss the major drivers that can affect efficiency of global health programs for developing countries. These drivers are in the form of DEA input and output variables (3.1), environmental factors (3.2), and funding concentration (3.3).

3.1. Input and output variables

We base the selection of input and output variables for DEA analysis on three criteria. One is the focus on the managerial efficiency of the delivery coordination between donors and country-level managers and its impact on the in-country downstream process. Another criteria is the consideration of both supply chain and health outcomes metrics as comprehensive performance metrics for global health supply chains (Glassman et al., 2013). The last criteria is the pursuit of simplicity in variable selection (Eichler and Levine, 2009). The latter criteria is reflected in the selection of only three variables: *landed costs* as input variable and two output variables, *Supply Timeliness* being an indicator of operational process performance and *Contraceptive Prevalence Rate (CPR)* a health outcome indicator for RH supply chains. Cost is a straightforward measure to represent observed expense of resources. Our specific input variable is landed costs of contraceptive deliveries per capita. We define supply timeliness as the number of days between the average transit delay of the country at hand and the average transit delay of the country of the sample with the largest transit delay. CPR of modern methods is defined as the proportion of women of reproductive age who are married or in a union and who are currently using (or whose partner is using) a modern contraceptive method. Of the possible measures of RH outcomes that have been used in the literature (such as adolescent birth rate, unmet need for family planning and undesired fertility rate, etc.) (Loaiza and Blake, 2010), we select CPR of modern methods as our health outcome variable because it directly captures the usage and availability of the delivered products and there is a reasonably complete current data set across our country set. These three chosen DEA variables are described in detail in Appendix A. Summary statistics are also provided in the online supplement (Table S1).

3.2. The impact of environmental factors on efficiency

The performance of a DMU relative to the maximum achievable efficiency is dependent on its level of input resources and output values. Nonetheless, researchers are aware that there are other phenomena that influence these input and output values besides managerial competence. The DMUs in this study are the countries, where each country is represented by a set of country-level RH programs. Some countries will have a unique program while others will have multiple programs. To generate a fair comparison across countries, country level factors that are not within the control of the program managers of the DMU should be considered exogenous, but should be controlled for, when assessing managerial efficiency. Typically, exogenous variables are classified as representing environmental factors and random shocks (Fried et al., 2002). While random shocks are arbitrary phenomena out of the control of anyone (e.g., good and bad luck, natural disasters, omitted variables, or statistical noise), environmental factors deserve special attention because they are under the control of other authorities and efficiency can be potentially improved if resources are devoted to modify these factors.

In the context of measuring health care delivery efficiency at the country level, the impact of cross-country heterogeneity has been studied (WHO, 2000). Evans et al. (2001) claimed that income per capita does not directly contribute to health outcomes, but suggested other measures of health expenditure and education. Other authors question this claim and find persistent significance between income per capita (measured by GDP per capita) and inefficiency (Gravelle et al., 2003; Greene, 2004). Given this debate, we include GDP per capita and public health expenditure as potential environmental variables of our analysis.

Next, we consider potential environmental factors that can impact our two output variables. The relationship between female education and contraceptive use is well-established by studies that use the demographic health survey (DHS) and are centered on Sub-Saharan Africa (Ainsworth et al., 1996; Kravdal, 2002). The socioeconomic factors most commonly used to study the uptake of modern contraceptive methods are parity, education, and household socioeconomic status factors Stephenson et al. (2007). Since GDP per capita is already included in our pool of environmental factors, we use a proxy for education (adult female literacy) as potential environmental factor that might impact efficiency.

A measure of lead time is our second output measure.[4] Empirical studies show a link between lead time performance and factors such as information technology and process improvement (Ward and Zhou, 2006). Furthermore, researchers claim that a country's logistics performance index (LPI) (Hausman et al., 2013) and whether the country is landlocked (Arvis et al., 2007) affect total landed costs (our input variable). Given this background, we select three additional environmental factors that can potentially impact efficiency: LPI, a proxy of trade level (merchandise index), and a proxy of location (landlocked country or not).

All the cited literature suggests that there might be a significant impact of environmental factors on efficiency in the context of our data sets. We claim it is vitally important to understand this impact and compensate for it in order to develop a fair process to compare managerial performance across countries as stated earlier. To understand the significance of these environmental variables and estimate magnitude of its impact, we posit the following hypothesis:

Hypothesis 1. *Environmental factors have a significant impact on efficiency of RH programs in Sub-Saharan Africa.*

We claim that this hypothesis represents the first step towards a fair process to isolating managerial inefficiency and provide our DMUs with useful insights for improvement. We also claim that, if this hypothesis is validated, policy agendas focused on changing environmental factors can improve RH program efficiency.

3.3. The impact of funding concentration on managerial efficiency

There is an increasing number of donors involved in health programs, where smaller amounts of aid are managed by more donors. Naturally, if efforts are not coordinated the efficiency, equity and effectiveness of these programs will suffer (Buse and Walt, 1996). So, the general theoretical claim is that the presence of multiple donors and lack of coordination negatively impact efficiency. Bigsten (2006) states that, in the presence of donor fragmentation, the focus of donor governments shifts to keeping the aid flowing rather than focusing on deployment's efficiency. Thus, Platteau (2004) observes that while a sole donor can influence a local leader, when there are many donors, competition to influence

[4] In fact, our measure is timeliness, the opposite of lead time, because any DEA output variable should have a positive relationship with efficiency.

the local leader ensues and this will imply lower access to beneficiaries. In addition, donors may free ride off the efforts of others by claiming credit (Bigsten, 2006).

O'Connell and Soludo (2001) construct indirect measures to assess the impact of lack of coordination among donors on transaction costs. Using a Herfindahl concentration index, their results suggest that aid to Africa was more dispersed and likely to result in higher transaction costs, thus lowering efficiency. A related issue is also highlighted by Knack and Rahman (2007), who claim that the cost of donor proliferation is a 15%–30% reduction in aid due to the hiring of donor country contractors. Predictions from their model imply that bureaucratic quality will erode more for recipients with greater donor fragmentation, showing a significant impact in Sub-Saharan Africa.

In the area of operations management, the research that links donor fragmentation and operational efficiency is scarce. The closest work is Besiou et al. (2014) that study earmarked funding and how it causes a negative impact on disaster response programs in decentralized settings.

Nevertheless, a small pool of literature studies the downsides of donor concentration, where donor fragmentation could be more beneficial to recipient countries (Munro, 2005). In fact, fragmentation may contribute to increasing the provision of the public good, if donors can employ conditional aid contracts to influence domestic policy in the recipient country (Torsvik, 2005). Brown and Swiss (2013) highlight a possible negative consequence of donor concentration as donors quit countries to concentrate their efforts on fewer countries without appropriate coordination i.e., the creation of aid orphans (i.e. countries that are abandoned by donors). They also suggest that donors might face a “donor cartel” in their negotiations.

There is a small stream of literature that claims that donor concentration might lead to reduced negotiation power by recipient countries. Decisions by donors reflect their sovereign interests in the area of trade flows, terrorism, or migrant flows and may not lead to coverage of country requirements (Schulz, 2009). Also donors expect recipient countries to support donor interests in international politics by trading more with donors and this constrains recipient country choices (Bandyopadhyay and Vermann, 2013).

In this study we posit that the logistics of delivery could be negatively impacted by fragmentation due to prioritization and attention paid to specific flows. We also expect that a focus on the required steps to follow through with partners to influence use, and thus impact CPR, may be negatively impacted by donor fragmentation. We therefore test the following hypothesis:

Hypothesis 2. *RH country programs with larger donor fragmentation (i.e. low funding concentration) have lower managerial efficiency.*

Our results will provide an empirical measure of the impact of donor fragmentation on efficiency.

4. Data sources

The proposed methodology is applied to a publicly available data set: the Reproductive Health Interchange (RHI) data. This data is collected and made available by the Reproductive Health Supplies Coalition at the website (http://www.myaccessrh.org/rhi-home). The site provides information regarding RH purchase orders and associated donors funding the orders for each country. This permits us to capture the timing, volume and content data for all purchases, as well as the associated lead time from order to delivery.

Our RHI data set is composed of 44 Sub-Saharan African countries with 2012 data on RH product orders and shipment information. We have filtered data to consider all orders with a receipt date in 2012. This is the latest year with most complete data accounting for a total of 871 different orders. We have purposely created a cross-sectional data set of one year because this is the standard length of a funding round and it is the time used to benchmark and evaluate program performance, while at the same time assuring that the environmental conditions remain constant. Each country's landed costs, timeliness and funding concentration were obtained using the RHI data set. Our data set also includes country level data regarding environmental variables and CPR from sources such as the World Bank (WB) and the United Nations (UN).

5. Methodology

We apply the three-stage framework used by Liu and Tone (2008) with a few variations (online supplement Figure S1). Stage 1 of this method runs a DEA model with the appropriately chosen set of input and output variables. The efficiency scores obtained in stage 1 capture the effects of all sorts of efficiency drivers, but the objective is to isolate the managerial efficiency from other drivers. To do so, the slack values of the inefficient DMUs are extracted. In stage 2, these slack values are used to run a SFA model and to decompose the effect of inefficiency between three different causes: environmental, random shocks and managerial. In stage 3, the output variables are adjusted for the environmental factors and random shocks and the DEA model is run again. Stage 3 results allow us to identify managerially efficient countries as well as the associated reference sets for inefficient countries. Our methodology employes a different DEA technique than the one suggested by Liu and Tone (2008) and we employ an additional tuning technique for readjusting the output variables prior to stage 3 suggested by Tone and Tsutsui (2006).

As noted before, each DMU of our analysis is represented by the set of managers that run each country-level RH program. We used the Open Source DEA (OSDEA-GUI) to run DEA, and Stata with *sfcross* command to run SFA (Belotti et al., 2013).

5.1. Stage 1: initial DEA analysis

In stage 1 and stage 3 of our methodology, we use the Slack-based Measure output-oriented model of DEA under variable returns to scale (SBM-O-V) approach. SBM is preferred because it directly minimizes slacks (i.e. input excess and/or output shortage), is unit-invariant for the different input and output variables, and is monotonically decreasing in each input and output slack (Cooper et al., 2007). Variable returns to scale is assumed since we suspect that not all instances of input increments will results in proportional changes in outputs. We use an output-oriented model to find ways to maximize output performance (i.e., minimize output shortage) given fixed input values. The corresponding optimization model that estimates the efficiency of each DMU (j), using standard approaches, can be expressed as follows:

$$\min_{\vec{\lambda_j}, \vec{s_j}} \rho_j^* = \frac{1}{1 + \frac{1}{n}\sum_{i=1}^{n} s_{ij} \Big/ y_{ij}} \tag{1}$$

$$x_{hj} \geq \sum_{j'=1}^{m} x_{hj'} \lambda_{j'j}, \; \forall h = 1, \ldots, l \tag{2}$$

$$y_{ij} = \sum_{j'=1}^{m} y_{ij'} \lambda_{j'j} - s_{ij}, \; \forall i = 1, \ldots, n \tag{3}$$

$$\sum_{j'=1}^{m} \lambda_{j'j} = 1 \quad (4)$$

$$\vec{\lambda_j}, \vec{s_j} \geq 0, \quad (5)$$

where ρ_j^* is the optimal efficiency value (or score) of country j, parameter x_{hj} is the h-th input quantity of the DMU at hand, parameter y_{ij} is the i-th output quantity of the DMU at hand, decision vector $(\vec{\lambda_j})$ is the intensity vector and decision variable s_{ij} is the slack variable of i-th output to the DMU in hand. One assumption of the model is that $y_{ij} \geq 0$, $\forall$ i. The objective function of the model (1) is a fractional equation where the efficiency score of DMU j is represented to be inversely related to the sum of inefficient indicators (slacks) of each output i. The sets of constraints (2) and (3) define input and output values of j, where the slack variables of all outputs are explicitly defined. Constraint (4) imposes the condition to introduce variable returns to scale.

5.2. Stage 2: SFA analysis

As described earlier, environmental variables refer to endowed variables for a country that the program manager cannot change. To this end, our environmental variables describe macroeconomic and market conditions in a country. In addition, the data used in DEA empirical studies typically involve noise and this is controlled by separating for statistical noise. We assume that the observed inefficiency effect (s_{ij}/y_{ij}) is a function of the true managerial inefficiency $(\hat{s}_{ij}/\hat{y}_{ij})$, environmental factors $(f(env))$ and the effects of statistical noise (v), where $s_{ij}/y_{ij} = \hat{s}_{ij}\hat{y}_{ij} + f(env) + v$. Thus, we follow Liu and Tone (2008) to formulate the cost frontier model as follows:

$$\frac{s_{ij}}{y_{ij}} = \beta_{io} + \sum_{k=1}^{K} \beta_{ik} lnz_{kj} + v_{ij} + u_{ij}, \quad (6)$$

where β_{io} is the intercept, β_{ik} is the coefficient estimate of the regression, z_{kj} is the k-th observable environmental factor of DMU j-th, v_{ij} represents the statistical noise (i.e. idiosyncratic random shocks), and u_{ij} represents the managerial inefficiency $(\hat{s}_{ij}/\hat{y}_{ij})$. The model assumes that $v_{ij} \sim N(0, \sigma^2_{v_{ij}})$.

Heteroscedasticity is very likely to appear in both types of errors (v_{ij} and u_{ij}). Thus, to correct for this issue we use the doubly heteroscedastic SFA model by employing the specification designed by Hadri (1999) that assumes $u_{ij} \sim N^+(0, \sigma^2_{u_{ij}})$ to define the variances of v and u as the following variance equations $\sigma^2_{v_{ij}} = \sigma^2_v exp(\delta_i^{'} W_j)$ and $\sigma^2_{u_{ij}} = \sigma^2_u exp(\gamma_i^{'} P_j)$, in which W and P are matrices that contain regressors that explain the variance behavior (i.e. variance regressors). From Kumbhakar (2003), these variables cannot be correlated with the environmental variables in Z.

In Table 1 we list the environmental variables that were first introduced in section 3.2. In addition, population and density are the two variables selected as variance regressors for the random shock error, where population has been selected since heteroscedasticity in the symmetric error component is usually related to the size of the DMUs. The variance regressor for the managerial inefficiency error is a popular measure of funding concentration based on the Herfindahl-Hirschman Index (HHI) (Knack and Rahman, 2007). Other potential primal and variance regressors have been considered but later discarded either to avoid overfitting or due to being strongly correlated with some of the current primal regressors violating Kumbhakar (2003) correlation's caveat. All independent variables are described in Table 1 and some of them are further described in Appendix A. Summary statistics of all independent variables are provided in the online supplement (Table S2).

After the estimations, it is straightforward to derive the residuals ($\varepsilon_{ij} = s_{ij}/y_{ij} - \beta_{io} - \sum_{k=1}^{K} \beta_{ik} lnz_{kj}$), which are the estimates of the error terms $v_{ij} + u_{ij}$. However, the decomposition into separate error components is more challenging. Jondrow et al. (1982) suggest $E(u|\varepsilon) = \frac{\sigma\Lambda}{1+\Lambda^2}\left(\frac{\phi\left(\frac{\varepsilon\Lambda}{\sigma}\right)}{1-\Phi\left(\frac{\varepsilon\Lambda}{\sigma}\right)} - \varepsilon\Lambda/\sigma\right)$ as the point estimate to draw inferences about the managerial inefficiency component (u) of a half-normal distribution. $\Lambda = \sigma_u/\sigma_v$, $\sigma^2 = \sigma^2_u + \sigma^2_v$, and $\Phi(\bullet)$ and $\phi(\bullet)$ are the standard normal cumulative distribution and density functions, respectively. We implement this extensively used procedure to decompose the residuals.

5.3. Stage 3: final DEA analysis

Since we have an estimate of the impact of environmental variables and shocks, we readjust the initial output values and run the SBM-V-O DEA model again. This step will get us a level playing field for countries because it will control for the uncontrollable variables. We recalibrate the output values by accounting for the environmental effects and random shocks from the initial values to obtain the adjusted output variables $y^a_{ij} = y_{ij}(1 + \beta_{io} + \sum_{k=1}^{K} \beta_{ik} lnz_{kj} + v_{ij}) = y_{ij}\left(1 + \frac{s_{ij}}{y_{ij}} - u_{ij}\right)$.

Additionally, Tone and Tsutsui (2006) propose a tuning formula that we apply to y^a_{ij}, $y^A_{ij} = \frac{\max_j y_{ij} - \min_j y_{ij}}{\min_j y^a_{ij} - \min_j y^a_{ij}}(y^a_{ij} - min_j y^a_{ij}) + min_j y_{ij}$. This method preserves the same ranking of the adjusted variables and keeps the same range of the original output values.

After adjusting for the environmental variables and random shocks, we run the DEA optimization model described in (1)–(5). We employ notation $(\bullet)^A$ to indicate that all variables employed in this model refer to stage 3 new readjusted values.

6. Empirical analysis

In this section, we provide the numerical results obtained from running the model and we test whether our hypotheses are supported by our results.

6.1. Numerical results

We ran the three stage approach with our data set described earlier. The initial DEA results, in stage 1 of our analysis, show that seven countries are on the efficient frontier (refer to the second column of Table B.1). The rest of countries are considered inefficient and DEA provides a summary of the gap, where gap is described as the current performance against a "best practice" performance by individual variable. In contrast, the final results obtained from our data set state that four of the seven efficient countries in stage 1 remain efficient at the end of stage 3 and there are seven new efficient countries (see the third column of Table B.1). These results suggest that some of the observed country level inefficiency can be attributed to environmental variables and random shocks. Thus, in Table 2, we observe that after adjusting for the environmental and statistical noise influences, the mean efficiency scores of countries improve while dispersion declines. This means that some of the variation in efficiency across countries can be explained by their heterogeneity of environmental variables and random shocks. In

Table 1
Independent variables.

Environmental variables	
- GDP per capita	- gross domestic product divided by midyear population
- Female literacy rate	- % female adults (ages 15 and above) who can read and write
- Landlock	- dummy variable for landlocked countries
- Public health expenditure	- % of public health expenditure from total health expenditure
- LPI	- Logistics Performance Index
- Merchandise	- % of sum of merchandise exports and imports divided by the GDP
Variance regressors for random shocks	
- Population	- total number of persons inhabiting a country
- Density	- midyear population divided by land area in square kilometers
Variance regressors for managerial inefficiency	
- Funding concentration	- sum of squares of market shares of the funding organizations

Table 2
Comparison of initial and final efficiency scores and slacks.

	DEA stage 1			DEA stage 3		
	Efficiency	CPR slack	Timeliness slack	Efficiency	CPR slack	Timeliness slack
Mean	0.535	28.456	15.864	0.870	3.847	8.558
St. dev.	0.263	17.512	15.916	0.198	7.658	12.441
Minimum	0.025	0	0	0.031	0	0
Maximum	1	53.407	73	1	40.130	53.112

particular, around 86% of CPR slack and 46% of timeliness slack are due to exogenous effects. Table B.1 shows the comparison between the initial and final country efficiency rankings.

The test for absence of heteroscedasticity in the regressions of both slacks gives small Chi square values, indicating that the specification of our model that corrects for heteroscedasticity has been effective. This is also corroborated by visual observation of the plots of the fitted values with the error terms. Furthermore, we discard endogeneity issues with the environmental variables (regressors) because there is no risk of reverse causality issues with the slack values due to the exogenous nature of these regressor variables. Other potential endogeneity issues are studied in Section 7.

The signs of the significant results for random shocks are all as predicted. In particular, under random shock errors (v_{ij}), the size of a country impacts the variance of statistical noise in both output slacks. In other words, larger populated countries have significantly larger variances in random shocks related to CPR and supply timeliness slacks than small countries. On the other hand, density has a negative relationship with the variance of random shock errors for both CPR and supply timeliness slack variables. The value of Λ for CPR slacks is relatively close to 1 indicating that the slacks are equally related to random shocks and managerial inefficiencies. In contrast, the value of Λ for supply timeliness slacks is small in magnitude, and this indicates that the managerial inefficiency impact is smaller than the one related to random errors.

6.2. *Discussion of hypothesis 1*

As support for hypothesis 1, we direct attention to the results in Table 3, which shows the SFA results by running regression equation (6) at stage 2. All of our environmental variable regressors have significant estimated coefficients for one or both slacks, with the exception of GDP per capita, which is not significant. The signs of all significant coefficients are consistent with expected behavior, except the sign of merchandise trade. In interpreting the signs, please note that the left hand sides of the regression focus on the slack associated with the variable, with a larger slack representing a greater distance to the efficient frontier.

The asterisks *, **, and *** indicate significance levels of 10%, 5% and 1% or better, respectively.

Table 3
Stochastic Frontier Estimation results.

	CPR slacks		Supply timeliness slacks	
	Parameter	Std. error	Parameter	Std. error
Environmental variables				
Constant	16.181***	1.877	0.655	0.651
GDP	−0.104	0.151	−0.002	0.026
Female literacy	−2.984***	0.374	0.038	0.051
Landlock	0.147	0.257	0.363***	0.139
Public health	−1.552***	0.281	−0.180**	0.083
LPI	−0.635**	0.295	−0.261***	0.056
Merchandise	1.351***	0.305	0.136*	0.073
Variance regressors for random shocks (v)				
Population	0.643***	0.198	2.942***	0.144
Density	−0.800***	0.225	−0.859***	0.228
Variance regressors for managerial inefficiency (u)				
Funding concentration	−12.201*	6.298	−22.351***	7.870
Λ	0.333	N/A	0.014	N/A
$E(\sigma_u)$	0.376	N/A	0.041	N/A
Log-L	−60.943	N/A	−43.220	N/A
Observations	44	N/A	44	N/A

While public health expenditure is significant for both output variables, GDP per capita is not a significant variable in our analysis. This is aligned with the WHO report (Evans et al., 2001; WHO, 2000), that claimed that the possible income per capita impact on health outcomes is not direct and it is only existent via the health expenditure effect (section 3.2).

Female literacy is the most significant socio-economic factor affecting CPR in our study and, understandably, it has no effect on lead time performance. This is a key socio-economic factor that directly influences improvements in RH as noted while motivating our hypothesis 1 (section 3.2). Similarly, another expected result from our analysis states that the logistics performance index (LPI) is significant for both operational process performance (timeliness slack) and health outcome (CPR slack). Note that LPI is a composite of different drivers related to the logistics capability of a country (Appendix A).

One advantage of our methodology is that it allows us to posit all environmental variables to influence performance without prior knowledge of the directions of their impacts on the output slacks. In this regard, our results are as expected for all our variables except for merchandise trade where, surprisingly, there is a negative significant relationship between merchandise trade and timeliness and CPR. We can find a reason for this effect in Dani Rodrik's work related to trade policy and economic growth in Sub-Saharan Africa. This research claims that an excessive emphasis on trade liberalization can backfire on economic growth if the scarce resources of local governments are not directed to the right measures (Rodrik, 1998). For developing countries, a larger merchandise trade percentage might imply larger imports raises than export raises causing an imbalance in trade and payments. This can constraint economic growth and living standards (Santos-Paulino and Thirlwall, 2004), where the demand of RH commodities might be directly impacted.

Our empirical results highlight that environmental conditions and random shocks play an important role in evaluating RH country level efficiency in the Sub-Saharan region and should be taken into consideration. Once the analysis accounts for these factors, the purportedly inefficient countries appear to do the best they can given their endowed parameters. This does not mean that improving the values of the environmental parameters should not be a goal, but rather, in the short term, such changes cannot be expected to materialize and are not the direct responsibility of the DMUs.

6.3. Discussion of hypothesis 2

We next focus on hypothesis 2 by examining Table 3 which shows that under inefficient managerial errors (u_{ij}), countries with high funding concentration (i.e., fewer donors) have significantly smaller managerial inefficient error variances in both CPR and supply timeliness slacks. In other words, countries with a higher funding concentration are linked to less managerial inefficiency variance for both output variables. We next examine summary statistics to check if these results are indicators of a possible influence of funding concentration on managerial inefficiency. The correlation between stage 3 efficiency scores and funding concentrations is 0.680 and there is a significant negative correlation of −0.659 between funding concentration and supply timeliness slacks and a negative correlation of −0.498 with respect to CPR slacks. Fig. 1 depicts a scatter plot of this relationship. Additionally, we can see an impact of funding concentration on efficiency, where for the set of efficient countries the funding concentration has mean = 0.956 and st. dev. = 0.076, while for the set of inefficient countries these values are mean = 0.585 and st. dev. = 0.215. While this provides statistical support to state that we cannot reject hypothesis 2, in order to formally accept this hypothesis, we perform some robustness and endogeneity checks in the next section.

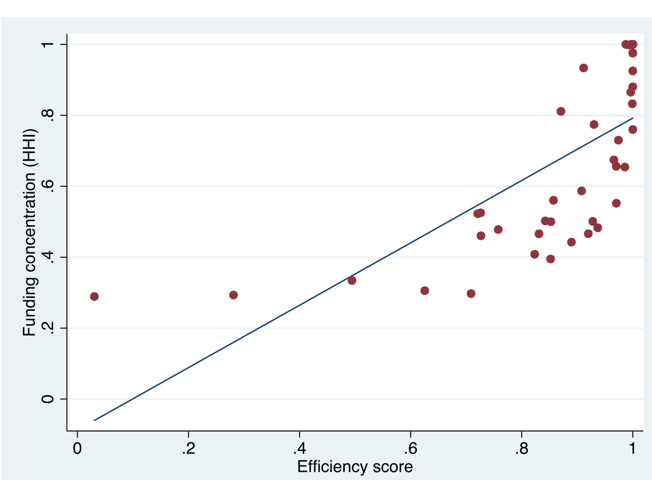

Fig. 1. Objective values and funding concentration (HHI) of the 44 countries.

7. Robustness and causality checks

We conduct robustness checks to strengthen and support our hypotheses. First, we use a different definition of our measure of funding concentration to test whether the results remain significant. Second, we regress with other environmental regressors that we did not include in the previous section. And third, we run experiments for years 2011 and 2010. Next, we corroborate the causal relationship between funding concentration and efficiency while, at the same time, we test to rule out possible drivers of efficiency that could compete with funding concentration. These possible drivers are the level of dominance of a specific donor and the size of the country.

7.1. Alternative definition of funding concentration

The most common alternative definition of funding concentration to the Herfindahl-Hirschman Index (HHI) is simply the number of donors that participate in the country's program (Knack and Rahman, 2007). This measure reduces the effect of the relative differences between each donor's funding shares. The value range and direction of this measure are also different than that of the HHI measure, where the larger this measure value is the less funding concentration. The correlation between HHI and this new measure is −0.75. Estimation results using this alternative proxy of funding concentration provide very similar estimates in stage 2. This measure remains statistically significant as the variance regressor of inefficient managerial errors, where high funding concentration (i.e., lower number of donors) have significantly smaller error variances in both CPR and supply timeliness slacks (online supplement Table S3). Furthermore, efficiency scores in stage 3 using this alternative measure of funding concentration have a correlation coefficient of 0.95 with the efficiency scores obtained using HHI as the funding concentration measure and a correlation factor of 0.07 with stage 1 efficiency scores. This indicates that our main results that support hypothesis 1 and 2 remain robust to this perturbation.

7.2. Other environmental regressors

Due to the size of the sample and potential overfitting issues, we have used a reduced but representative set of environmental regressors. In order to show the robustness of the SFA results to the influence of environmental factors, we provide the stage 2 results obtained from employing some alternative environmental variables popular in the global health literature. In particular, we show results employing the Gini coefficient, instead of the female literacy rate (the correlation between these two variables is 0.56) and the corruption index instead of the GDP per capita (the correlation between these two variables is 0.37). The major results related to our hypotheses remain unaltered. Both regression tables are provided in the online supplement (Tables S4 and S5).

7.3. Other years

Repeating the empirical study for other years has allowed us to verify that our hypotheses are also robust throughout time. From the same data sources described in Section 4 we have created the corresponding data sets for years 2011 and 2010 (most of the macroeconomic values for 2013 are not published yet). hypothesis 1 is tested and corroborated for both years, where multiple coefficients are significant with the same sign as our results for the 2012 data set. In addition, the mean efficiency scores from stage 1 to stage 3 improve while dispersion declines for both years. Related to

Table 4
OLS regressions with managerial efficiency as the dependent variable.

	Model 1		Model 2		Model 3		Model 4	
	Parameter	Std. error	Parameter	Std. error	Parameter	Std. error	Parameter	Std. error
HHI	0.557***	0.088					0.612***	0.142
UNFPA			0.264***	0.082			−0.065	0.096
Population					−0.060***	0.019	−0.002	0.020
R-squared	0.490	N/A	0.197	N/A	0.192	N/A	0.495	N/A

Note: we are using log(population) as the proxy of size.

hypothesis 2, we also observe an influence of funding concentration on managerial efficiency, where the correlation coefficients between stage 3 efficiency scores and HHI are positive with a value of 0.633 for the 2011 data set and 0.262 for the 2010 data set. More details of the 2010 and 2011 experiments are available upon request.

7.4. Tests to corroborate the causality relationship between funding concentration and efficiency

In order to accept hypothesis 2, we need to study possible endogeneity issues between funding concentration (HHI) and stage 3 efficiency scores (i.e. each country's managerial efficiency). One might argue that from the obvious correlation of these two variables it can not be asserted that low funding concentration is a direct cause of managerial inefficiency and that this relationship could actually be mainly due to the opposite effect in which the distribution of donor share per country is a consequence of a country's managerial efficiency. To prove the causal relationship stated in hypothesis 2 we run a linear OLS regression between these two variables, where HHI is the independent variable and managerial efficiency the dependent variable (Model 1 of Table 4). This relationship is significant at the 1% level and the regressor is uncorrelated with the error term of this regression providing no evidence of endogeneity issues in this relationship.

Furthermore, one could think that instead of funding concentration, the underlying driver of managerial efficiency is the level of dominance of a specific donor (i.e. proportion of share of funds of a specific donor with respect to others). We next look at the nature of this funding mix per each country. Fig. 2 shows this mix for our 2012 RHI data set where there are two major funding organizations the United Nations Population Fund (UNFPA) and the U.S. Agency for International Development (USAID) and the rest of them only represent around 11% of overall donations. UNFPA has a larger presence in small and less populated countries, where the overall need of funds can be solely covered by this funding organization. On the other hand, USAID's presence is in medium and large size Sub-Saharan countries and it is always shared with other donors (online supplement Table S6). Since UNFPA and USAID presence is substitutive (both vectors of shares have a correlation of −0.9), we only analyze the influence of UNFPA presence related to managerial efficiency and funding concentration. The correlation coefficient of the share of UNFPA per country with efficiency is 0.493. This might imply that UNFPA practices with in-country managers program managers lead to efficiency but there is also a strong positive correlation (0.814) between funding concentration (HHI) and the share of UNFPA per country. Indeed, there is a causal relationship between UNFPA share and managerial efficiency (Model 2 of Table 4). For this reason, one could posit that the causal relationship between HHI and managerial efficiency is indirect and occurs through the causal relationship between UNFPA and managerial efficiency. Likewise, a strong correlation can also be observed with the size of the country (Model 3 of Table 4). We only need to regress all three variables together to corroborate the direct causal relationship between funding concentration and managerial efficiency and discard the possible competing relationships related to UNFPA share and country's size with managerial efficiency (Model 4 of Table 4).

8. Benchmarking process: learning from best practices

The final DEA analysis provides information that allows us to group DMUs in reference sets for benchmarking. Section 8.1 provides the details on how to build these sets. For each set, Section 8.2 suggests a supply chain framework to provide guidance on how to derive the most appropriate best practices. Finally, Section 8.3 illustrates this benchmarking process with two countries.

8.1. Reference and extended reference sets

For each country not on the efficient frontier, an output shortfall (s^A_{ij}) for each of the output variables, CPR and timeliness, is generated. This variable is defined as $s^A_{ij} = \sum_{j'=1}^{m} y^A_{ij'} \lambda^A_{j'j} - y^A_{ij} \geq 0$, where i is related to the output variable. Intuitively, the magnitude of this shortfall suggests the opportunity for improvement by describing the maximum attainable performance (the frontier) given resource inputs, outputs, and other determinants that affect the country's performance. This formula directs the manager to a subset of efficient countries to look at, which are the countries that have a positive value of $\lambda^A_{j'j}$, where $\vec{\lambda}^A_j$ is the intensity vector. This set of efficient countries is called the reference set (or peer set) of DMU j, and it is formally defined as follows.

Definition 1 A reference set of country j is $E_j = \{j' \,|\, \lambda^A_{j'j} > 0, j' \in (1, \ldots, m)\}$.

Reference sets are useful to program managers of countries that are considered to be inefficient because they are a good source of best practices. Table B.2 provides the reference set and intensity component values per each country. Nonetheless, in practice and given hypothesis 1, having similar environmental conditions is a factor that can be included to provide a more useful reference set to the practitioner of the country at hand:

- Practitioners might prefer to learn from other countries in the efficient frontier than the countries in their reference set if the former countries have closer environmental conditions to the country at hand.
- Furthermore, not only efficient countries can be useful references. At times, other inefficient countries closer to the efficient frontier than the country at hand that have similar environmental conditions could be more useful references.
- If the country at hand is already efficient it should also sustain and try to improve its efficiency level. In this case, suggesting a reference for this efficient country can be useful.

To provide a flexible definition of reference sets that incorporates these additional aspects, we have defined *extended reference sets* for each country as follows.

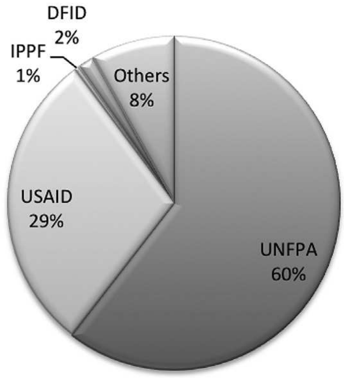

Fig. 2. Pie chart of 2012 RHI data set donor share (HHI). Note: Besides UNFPA and USAID, the rest of organizations in the chart are IPPF (International Planned Parenthood Federation), DFID (U.K. Department for International Development), and Others includes organizations such as the country's Ministry of Health, the Global Fund, the United Nations Development Program (UNDP), the Marie Stopes International (MSI), DKT International, PSI and the German Development Bank (KFW).

Definition 2 *An extended reference set of an inefficient country j is* $ext(E_j) = E_j \cup \left\{ \tilde{j} \,\middle|\, \frac{s^A_{i\tilde{j}}}{y^A_{i\tilde{j}}} \leq \frac{s^A_{ij}}{y^A_{ij}} \forall i \text{ and } d(j,\tilde{j}) < d(j,j') \forall j' \in E_j \right\}$, *where* $d(j,\hat{j}) \in R^n$ *and each component of this vector is the euclidean distance between DMU j and* $\hat{j}$ *fitted values of stage 2 regression* $(d_i(j,\hat{j}) = \sqrt{\sum_{k=1}^{K} \beta_{ik}^2 (lnz_{kj} - lnz_{k\hat{j}})^2})$.

Definition 3 *An extended reference set of an efficient country j is* $ext(E_j) = argmin\{\sqrt{\sum_{i=1}^{I} d_i(j,\tilde{j})^2}\ \forall \tilde{j} \text{ in the efficient frontier except } j\}$.

Table B.2 shows the DMUs that are added to the reference set to compose the extended reference set for each country. For example, Rwanda has been added in the extended reference set of Malawi. This is because Rwanda, despite being an inefficient country, is closer to the efficient frontier than Malawi and Rwanda's environmental variables are closer to Malawi than the ones of its reference set (Lesotho and Sudan). This can be a useful addition because Malawi's RH program managers might be able to learn more from Rwanda's RH program's best practices than from Lesotho's and Sudan's. As expected, countries with a lower efficiency score or similar environmental characteristics than others have a larger extended reference set.

8.2. Benchmarking process

Any country trying to improve performance has to figure out concrete steps, both process and system based. We suggest a supply chain framework, such as the one described in Kretschmer et al. (2014) for school feeding programs across less-developed countries, to help systematically identify concrete steps for process improvement. Kretschmer et al. (2014) classify each country's program as Centralized, Decentralized or Semi decentralized, and whether or not the programs were insourced or outsourced. However, for the context of RH programs, we suggest a focus on the extent of coordination, instead of centralization. Their paper describes external factors and internal factors to understand the logic for the choice of supply chain structure and its alignment with goals. Our definition of environmental variables is similar to their definition of external factors and the aggregate efficiency of their internal factors is captured by our quantitative measure of managerial efficiency. So, at the benchmarking step, and given that managerial efficiency scores do not account for environmental factors, the focus of this process should only be on internal supply chain factors. In the next section, we foreshadow an approach to learning for benchmarking by using this suggested supply chain framework in the context of two countries, Botswana (inefficient) and Lesotho (efficient).

8.3. Case study: Lesotho and Botswana

Botswana and Lesotho are landlocked countries in southern Africa with a similar population of 2.1 million people and 2 million people, respectively. Both countries are among the countries with the highest prevalence of HIV/AIDS in the world. While Botswana is considered a middle-income country (GNI per capita US $7480 in 2011) with a stable and democratically elected government, Lesotho is classified as a lower middle income country (GNI per capita US $1220 in 2011). If we look at the stage 1 efficiency scores of these two countries (in Table B.1), Botswana has a 72.08% score while Lesotho's score is slightly lower at 68.5%. Yet, after adjusting for environmental conditions and random shocks, our empirical analysis situates Lesotho on the efficiency frontier, and Botswana as a managerially inefficient country with an estimated efficiency of 70.5%. Botswana's reference set includes Lesotho with an 84.9% weight in the projection to the frontier and the remaining 15.1% weigh assigned to the other country in its reference set, Sudan (see Table B.2).[5] Given that Lesotho is the dominant reference of Botswana, we provide an evaluation of both countries' general health care and RH structural and operational managerial initiatives. This analysis briefly explores an approach to learning that could trigger process oriented steps for Botswana to generate better outcomes for the same level of funding.

8.3.1. Can Botswana learn from Lesotho?

By following our suggested benchmarking framework (8.2), a summary of the differences between Lesotho and Botswana supply chain and operational initiatives is shown in Table 5. It suggests that despite both countries dealing with multiple RH donors, Lesotho follows a well-defined coordination strategy via the Development Partners Consultative Forum (DPCF)[6] while Botswana does not have an entity or forum with this clearly defined goal Report (2011). Similarly, public-private partnerships (PPPs), procurement, and the logistics of commodity and information flows seem to be functioning well in Lesotho. This is thanks to the following respective mechanisms: private health clinics and hospitals (CHALs)[7] integrated with the government facilities via Standard Operating Procedures (SOPs), a procurement coordinator (NDSO),[8] and a well-functioning Logistics Management Information System (LMIS) system. In Botswana there is an LMIS, but information flow from health facilities is not robust (Brown, 2013). This is due to its new supply chain structure (set up in 2010) that transitioned to a more decentralized model, where health administration in the districts is the responsibility of District Health Management Teams (DHMTs). As a result, there is a lack of clarity on how information flows (Report, 2011).

We suggest that Botswana's health supply chain managers can explore adjustments to their system by comparing their choices to Lesotho. Many of these process oriented steps reflect choices that are worth serious consideration. Similar processes could be evolved

[5] Due to Botswana's relative proximity to the efficient frontier and its relative similarity in terms of environmental conditions with its countries in the reference set, the extended reference set remains the same as its reference set.

[6] a platform for donor coordination, alignment, and harmonization created by the Government of Lesotho and some of its partners.

[7] Christian Health Associations of Lesotho.

[8] the National Drug Supply Organization.

Table 5
Summary of the differences in RH supply chain practices in Lesotho and Botswana.

Attribute	Coordinated	Partly coordinated	Uncoordinated	Lesotho notes	Botswana notes
Funding fragmentation	Lesotho	–	Botswana	HHI = 0.76	HHI = 0.52
Donor coordination	Lesotho	–	Botswana	Well defined roles (DPCF)	No clearly defined roles
Public-Private partnerships	Lesotho	–	Botswana	CHAL facilities common SOPs	Non public facilities not integrated
Procurement	Lesotho	Botswana	–	Commodities supplied by NDSO	Centralized erratic availability CDC (2008)
Commodity and information flows	Lesotho Mwase et al. (2010)	Botswana	–	LMIS functioning well	New DHMT system lacks clarity

for all countries, thus enabling a virtuous cycle of improvement that can lead to better supply chain performance and better health care outcomes. Nevertheless, the success related to continuous improvement is not automatic after identifying best practices, we should note that the facilitation of best practice transfer is the key to success. Our exploration suggests that more detailed data regarding process based learning to enable efficiency improvement is a working direction to pursue.

9. Managerial and policy insights

The empirical analysis and benchmarking process suggested in this paper present several steps that can be taken to improve the performance of global health supply chains in Sub-Saharan Africa. This section complements the previous ones by providing further managerial and policy insights to the different stakeholders of this type of supply chains. For further dissemination, a policy paper targeted to practitioners and related to this academic work has been created by the authors jointly with the Center for Global Development (Iyer et al., 2015).

9.1. In-country program managers: learning from benchmarking

The benchmarking process presented in Section 8.2 provides a systematic tool that can help the in-country managers identify best practices from the extended reference set. While there are some overall accepted good practices, we should note that other best practices might work for a few DMUs but not for others. For this reason, the emphasis should be on following a good benchmarking technique that can generate recommendations rather than directly following a list of suggestions. In the field of supply chain management there are some established best practices known to foster managerial efficiency improvement. For example, the use of a common information system to track all flows regardless of donor and to coordinate all procurement. In Lesotho, for example, despite the presence of over 15 donors, an enterprise resource planning system to track flows and the supply of commodities to health facilities is done by the NDSO.

Going from the estimate of efficiency to improving performance requires country level participation. In this direction, we expect an increased use of collaboration across developing countries to improve outcomes in global health supply chains. There is a plan to create centers for excellence that would foster such collaboration, as the current plans for establishing an East African regional center for excellence in health, vaccines and immunization logistics (in Rwanda).[9] As a way forward, we hope to see exploration of peer country collaborations at such regional centers of excellence.

[9] http://venturesafrica.com/rwanda-tasked-with-pioneering-ehealth-for-east-africa.

9.2. Donors: lessening the impact of donor funding fragmentation

Our analysis supports past literature that summarized the detrimental impact of aid fragmentation on managerial efficiency (Section 3.3). Most importantly, our paper is one of the very few papers that provides empirical evidence of this claim. The magnitude of the coefficients in Table 3 shows the specific quantitative impact of this fragmentation on overall managerial efficiency. This result suggests that dealing with the impact of funding fragmentation can permit significant benefits to managerial efficiency even with the same level of funding. For the authors, this result is a pleasant surprise, but also suggests immediate noninfrastructure solutions to try to improve performance. From our case study, literature search, and conversations with practitioners, we suggest the following specific donor best practices:

- Increase the communication between donors and in-country program managers of the same country and across countries in the same region. The creation of the centers of excellence funded by the donors and described in 9.1 is a good example.
- Increase the communication between different donors without changing donors' shares. Sarley et al. (2014) describe Coordinated Supply Planning (CSP) - an attempt to coordinate across donors like UNFPA and USAID to create joint forecasts for planning shipments and for coordinating with manufacturers.
- Let a large donor or an external integrator represent the interests of the donor community and generate reports used by others (Kraiselburd and Yadav, 2013). We suggest that the experience from HIV drug delivery can serve as a guide to improving performance in the RH delivery space. For example, PEPFAR and the Global Fund now routinely collaborate to define priorities, funding streams and impact measurement. Such an approach could maintain efficiency while permitting the required number of donors to contribute (Bilimoria, 2012).
- While more difficult to implement, coordination by donors to focus on specific countries, based on past collaboration, may enable increased donor concentration for individual countries while maintaining the overall aid budgets. These ideas have been encouraged in the development aid literature and are termed “division of labor among donors” (Schulz, 2009). Such a system may well enable longer term planning and thus more stable processes over time. But it will require coordination between different donor organizations, as well as between local governments and international donors, and have seen limited realization in practice (Brown and Swiss, 2013).

9.3. Government actions: improving environmental variables

When examining performance of a supply chain in a country, it is clear that managers of the health programs have no control over most environmental factors such as whether a country is landlocked, female literacy levels, merchandise taxes, logistics performance index (LPI), etc. But as Table 3 shows, each of these factors impacts efficiency by impacting both CPR as well as timeliness. We translate the most significant results to the following recommended actions:

- The potential impact of an improved LPI on timeliness is clear in our results (Table 3) and has only recently been reported in the operations management literature. Hausman et al. (2013) show this result by examining the impact of delays at ports for custom clearance. For health products a fast track clearance can significantly reduce inventory in transit and enable higher in stock of products. In turn, availability of products can impact usage and drive up CPR as Table 3 shows (negatively-correlated significance between LPI and CPR slacks).
- It is also important to invest in public health because this positively affects both of our output measures (CPR and timeliness). Besides increasing public health care expenditure all together, studies such as Evans et al. (2001) claim that reallocating available resources from interventions that are not cost effective to those that are more cost effective but not fully implemented can also improve efficiencies.
- The significance of female literacy for reducing CPR slacks and thus improving efficiency provides a clear message. It suggests that it is important to educate the population regarding product use and benefit i.e., generate a demand for products along with a focus on supply.

Governments could use these results to justify improvements in infrastructure, investments in public health and education, reductions in unwanted fees and taxes, etc. by claiming that these actions would generate health related benefits.

10. Conclusions and future research

To our knowledge, our analysis of the RH data set and associated variables is the first cross-country global health benchmarking study done using a multi-stage DEA/SFA modeling technique. By providing a methodological framework that uses publicly available data, this analysis can be replicated for other contexts such as different types of cross-country global health programs and different geographical locations. In particular, our analysis of RH programs in Sub-Saharan Africa sheds some interesting insights. First, we observe that in evaluating managerial efficiency at the country level performance should be adjusted to reflect the impact of uncontrollable parameters. In other words, a country with a poor network of public hospitals cannot be compared to one with a modern public hospital network, thus its observed performance has to be handicapped for this difference. Once such external parameters are adjusted for, what remains are management controlled parameters, from which we can calculate the managerial efficiency of each country's set of RH programs. Furthermore, our analysis permits countries to be grouped into reference sets and extended reference sets, where the latter is a new notion designed to ensure a larger and more useful pool of benchmarking partners with similar environmental conditions. A supply chain framework approach is foreshadowed as a useful benchmarking process that can generate process based ideas for improvement.

We investigate the quantitative impact of some factors on efficiency to come up with useful managerial and policy recommendations. First, we provide information related to the impact of countries' socio-economic factors on efficiency. Our results state that, from our pool of environmental variables, public health expenditure and female literacy are the most significant factors that affect the uptake of modern contraceptives. On the other hand, the logistics capabilities of a country and public health expenditure are the most significant parameters influencing lead time. In this regard, our results are aligned with other empirical work that links policy making decisions with health and logistics outcome performance. Second, we find that funding concentration is a significant variable that positively influences managerial performance affecting delivery efficiency and RH outcomes. This result is a relevant contribution because evidence of such claim has barely been empirically studied. We suggests many different ways for donors and recipient countries to mitigate the detrimental impact of aid fragmentation.

Many research questions beyond those addressed in this paper may be answered using similar data sets. For example, one could run an input-oriented three-stage DEA/SFA model to focus on finding ways to optimize the allocation of donations (by minimizing the input excess) given fixed supply timeliness and CPR values. This problem setting is related to the donor's aid redistribution problem also known as the allocative efficiency problem. Another aspect to be studied is the learning effect of efficiency through different years using panel data.

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Supplementary information

Supplementary information related to this article can be found at http://dx.doi.org/10.1016/j.jom.2016.05.005.

Appendix A. Variable Descriptions

Input and output variables in DEA analysis

Landed costs per capita: the value in the RHI includes all landed costs, i.e. product unit or acquisition cost, freight costs, insurance costs, any sampling and testing costs and any service costs. We divide this quantity with 2012 population. Units: Current U.S $ per capita. Data source: RHI data set.

Supply timeliness: the difference in days between the maximum transit delay value across all DMUs and the transit delay for that particular country, where transit delay (TD) is the number of days between shipping date and actual receipt date. $supply\ timeliness_j = max_k TD_k - TD_j$, where $TD_k = receipt\ date_k - shipping\ date_k$ Units: Days. Data source: RHI data set. Data exception: Value for the country with maximum delay is 1 to avoid zero values.

Contraceptive Prevalence Rate (CPR): the proportion of women of reproductive age (from 15 to 49 age) married or in a union and who are currently using (or whose partner is using) a modern contraceptive method. Units: % of total women population of reproductive age. Data source: World Contraceptive Use 2012 (model-based estimates).

Independent Variables in SFA analysis

Gross Domestic Product (GDP) per capita: the sum of gross value added by all resident producers in the economy plus any product taxes and minus any subsidies not included in the value of the products. It is calculated without making deductions for depreciation of fabricated assets or for depletion and degradation of natural resources. Units: Current U.S $. Data source: World Bank.

Female literacy rate: total is the percentage of the female population age 15 and above ('adult') who can, with understanding, read and write a short, simple statement on their everyday life. Generally, literacy also encompasses numeracy, the ability to make simple arithmetic calculations. Units: % of total female ‘adult’ population. Data source: World Bank (the World Development Indicators).

Public Health expenditure: recurrent and capital spending from government budgets, external borrowing and grants (including donations from international agencies and NGOs), and social health insurance funds. Units: % of total health expenditure, where total health expenditure is the sum of public and private health expenditure. It covers the provision of health services, family planning activities, nutrition activities, and emergency aid designated for health but does not include provision of water and sanitation. Data source: World Bank.

Logistics Performance Index (LPI): reflects perceptions of a country's logistics based on efficiency of customs clearance process, quality of trade- and transport-related infrastructure, ease of arranging competitively priced shipments, quality of logistics services, ability to track and trace consignments, and frequency with which shipments reach the consignee within the scheduled time. Units: ranges from 1 to 5, with a higher score representing better performance. Data source: World Bank.

Merchandise trade: sum of merchandise exports and imports divided by the value of GDP, all in current U.S. dollars. Units: % of the GDP. Data source: World Bank.

Density: midyear population divided by land area in square kilometers. Population is based on the facto definition of population, which counts all residents regardless of legal status or citizenship-except for refugees not permanently settled in the country of asylum. Land area is country's total area, excluding area under inland water bodies, national claims to continental shelf, and exclusive economic zone. Units: any positive number. Data source: World Bank.

Funding Concentration: sum of squares of fund shares in $ value from each funding organization in a country. It is the Herfindahl-Hirschman Index (HHI) measure applied to describe the funding mix for a country $HHI_j = \sum_{h=1}^{n_j} share_{jh}^2$, where $share_{jh} = \frac{landed\ costs\ of\ donor\ h\ in\ country\ j}{total\ landed\ costs\ in\ country\ j}$ and n_j : total number of donors in country j. Units: ranges from a 1/N to 1, where N is the number of funders. Data source: RHI data set.

Appendix B. Additional Tables

Table B.1
Stage 1 and 3 score and ranking results.

DMU name	Objective Value Stage 1 (ρ_j^*)	Objective Value Stage 3 $(\rho_j^*)^A$	Ranking Stage 1	Ranking Stage 3
Angola	0.290	0.999	37	12
Benin	0.269	0.937	38	22
Botswana	0.708	0.721	11	3
Burkina Faso	0.404	0.970	28	20
Burundi	0.446	0.930	24	23
Cameroon	0.507	0.928	22	24
Central African Republic	0.310	1	34	1
Chad	0.214	0.970	43	19
Comoros	1	1	1	1
Congo, Rep.	0.597	0.996	20	14
Congo, Dem. Rep.	0.025	0.857	44	30
Cote D'Ivoire	0.334	0.920	31	25
Djibouti	0.616	1	16	1
Eritrea	1	1	1	1
Ethiopia	0.469	0.831	23	34
Gabon	0.539	0.974	21	18
Gambia, The	0.646	1	13	1
Ghana	0.406	0.852	27	32
Guinea	0.218	0.494	42	42
Guinea-Bissau	0.444	0.911	25	26
Kenya	0.721	0.625	9	41
Lesotho	0.685	1	12	1
Liberia	0.338	0.890	30	28
Madagascar	0.599	0.843	18	33
Malawi	0.737	0.758	8	36
Mali	0.257	0.987	40	17
Mauritania	1	1	1	1
Mauritius	1	1	1	1
Mozambique	0.298	0.966	36	21
Namibia	1	0.996	1	13
Niger	0.301	1	35	1
Nigeria	0.260	0.281	39	43
Rwanda	0.598	0.993	19	15
Sao Tome and Principe	0.711	0.871	10	29
Senegal	0.329	0.908	32	27
Sierra Leone	0.231	1	41	1
South Africa	1	0.031	1	44
Sudan	0.328	1	33	1
Swaziland	1	0.987	1	16
Tanzania	0.631	0.823	15	35
Togo	0.393	0.709	29	40
Uganda	0.428	0.852	26	31
Zambia	0.605	0.727	17	37
Zimbabwe	0.632	0.726	14	38

Table B.2
Reference sets and intensity component values.

DMU name	Reference (intensity value)	Extended references
Angola	Djibouti (0.463), Gambia, The (0.005), Sudan (0.531)	Mauritania
Benin	Comoros (0.220), Lesotho (0.064), Sudan (0.716)	Eritrea, Gambia, The, Mauritania, Angola, Mozambique
Botswana	Lesotho (0.849), Sudan (0.151)	–
Burkina Faso	Central African Republic (0.522), Lesotho (0.150), Sudan (0.328)	Mali
Burundi	Central African Republic (0.752), Lesotho (0.248)	Rwanda
Cameroon	Comoros (0.099), Mauritius (0.704), Niger (0.198)	–
Central African Republic	Central African Republic (1)	Gambia, The
Chad	Comoros (0.529), Mauritania (0.138), Niger (0.333)	–
Comoros	Comoros (1)	Eritrea
Congo, Rep.	Mauritius (0.360), Niger (0.640)	–
Congo, Dem. Rep.	Comoros (0.384), Lesotho (0.211), Sudan (0.405)	Cameroon, Eritrea, Mali
Cote D'Ivoire	Comoros (0.138), Lesotho (0.196), Sudan (0.666)	Angola, Eritrea, Gambia, The, Mauritania, Mozambique, Sierra Leone
Djibouti	Djibouti (1)	Comoros
Eritrea	Eritrea (1)	Djibouti
Ethiopia	Lesotho (0.548), Sudan (0.452)	Central African Republic, Chad, Niger
Gabon	Comoros (0.016), Lesotho (0.119), Sudan (0.865)	Mauritius, Namibia
Gambia, The	Gambia, The (1)	Central African Republic
Ghana	Lesotho (0.205), Sudan (0.795)	Angola, Cameroon, Comoros, Congo, Rep., Djibouti, Eritrea, Gabon, Gambia, The, Mauritania, Mauritius, Mozambique, Namibia
Guinea	Comoros (0.327), Lesotho (0.102), Sudan (0.571)	Angola, Benin, Cote D'Ivoire, Eritrea, Gambia, The, Mauritania, Mozambique, Senegal, Sierra Leone, Togo
Guinea-Bissau	Comoros (0.584), Lesotho (0.142), Sudan (0.273)	Cameroon, Gambia, The
Kenya	Lesotho (0.317), Sudan (0.683)	Angola, Cameroon, Comoros, Eritrea, Gabon, Ghana, Liberia, Madagascar, Mauritius, Namibia, Sao Tome and Principe, Tanzania
Lesotho	Lesotho (1)	Mauritania
Liberia	Comoros (0.204), Lesotho (0.285), Sudan (0.510)	Angola, Eritrea, Mauritania, Mozambique
Madagascar	Lesotho (0.479), Sudan (0.521)	Angola, Comoros, Eritrea, Gambia, The, Liberia, Mauritius, Namibia, Senegal
Malawi	Lesotho (0.687), Sudan (0.313)	Rwanda
Mali	Comoros (0.013), Lesotho (0.050), Sudan (0.937)	Central African Republic, Niger
Mauritania	Mauritania (1)	Djibouti
Mauritius	Mauritius (1)	Comoros
Mozambique	Central African Republic (0.746), Lesotho (0.150), Sudan (0.104)	Angola, Eritrea, Gambia, The, Mauritania
Namibia	Comoros (0.021), Lesotho (0.002), Sudan (0.977)	Mauritius
Niger	Niger (1)	Gambia, The
Nigeria	Comoros (0.516), Lesotho (0.220), Sudan (0.264)	Angola, Cote D'Ivoire, Eritrea, Liberia, Mauritania, Mozambique, Senegal, Togo
Rwanda	Central African Republic (0.565), Lesotho (0.036), Sudan (0.399)	Angola, Eritrea, Gambia, The, Mauritania
Sao Tome and Principe	Central African Republic (0.531), Lesotho (0.469)	Angola, Comoros, Cote D'Ivoire, Djibouti, Eritrea, Gabon, Liberia, Mauritius, Namibia, Rwanda, Sudan
Senegal	Central African Republic (0.279), Lesotho (0.387), Sudan (0.334)	Benin, Gambia, The, Mozambique
Sierra Leone	Sierra Leone (1)	Gambia, The
South Africa	Comoros (0.825), Lesotho (0.175)	Gabon, Ghana, Kenya, Madagascar, Mauritius, Namibia, Sao Tome and Principe, Swaziland, Tanzania
Sudan	Sudan (1)	Eritrea
Swaziland	Central African Republic (0.899), Lesotho (0.070), Sudan (0.031)	–
Tanzania	Lesotho (0.170), Sudan (0.830)	Angola, Cameroon, Comoros, Congo, Rep., Cote D'Ivoire, Eritrea, Gabon, Ghana, Mauritius, Namibia
Togo	Comoros (0.281), Lesotho (0.442), Sudan (0.277)	Angola, Benin, Cote D'Ivoire, Eritrea, Gambia, The, Liberia, Mauritania, Mozambique, Senegal
Uganda	Lesotho (0.542), Sudan (0.458)	–
Zambia	Lesotho (0.884), Sudan (0.116)	Burundi, Uganda
Zimbabwe	Lesotho (0.825), Sudan (0.175)	–

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