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by

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Abstract

The Stiglitz Report published in September 2009 has brought back to the attention of policy makers and researchers that measuring a country's development solely on the basis of GDP or GDP per capita is not sufficient. An early attempt at multidimensional measurement is the Human Development Index (HDI) developed by the United Nations Development Program in 1990. This measure consists of three components: a health index, an education index, and a standard of living index. Even though it was and still is subject to criticism, it is the only multidimensional measure that has been around for 20 years and is widely accepted by policy makers, who use this measure to compare the state of development of their country with those of other countries. They would like to maximize the HDI to improve their position in the ranking. As it is a multi-dimensional measure, it is necessary to influence different fields of development, which can be done by policy makers via public spending. We differentiate between public spending on education, health and general spending. This corresponds to the three components of the HDI. In Sub-Saharan Africa, which is the region of interest here, the total government budget is limited in most countries, so that the only option policy makers have is to allocate the given budget efficiently over the three categories. To find the best possible budget allocation, we use an optimum portfolio theory approach, which has been adapted to the problem at hand.

The approach consists of two stages. The first stage is concerned with the econometric estimation of a linear model that links variation in the policy instruments to the corresponding variation in the individual components of the HDI in a given general environment implicitly defined by a set of exogenous variables, such as the HIV-rate, colonial ancestry, and so on. Using the method of Seemingly Unrelated Regression, we estimate the contribution of each instrument to each target as part of a simultaneous equations system. As a bonus, we obtain the covariance matrix of the parameter estimates. In a second stage, we use these estimation results, including the covariance matrix of the parameter estimates, to define a portfolio-selection problem, known from financial optimum portfolio analysis. In our case, however, the distribution of a given budget of government expenditures over the various HDI components constitutes the portfolio selection problem, rather than distributing funds over a portfolio of financial assets. In our case, an efficient portfolio minimizes the variance (further called V) in the HDI for a given expected value of the HDI. We are able to calculate efficient HDI portfolios by varying the degree of risk-aversion over a preset range, and tracing the corresponding set of optimum portfolios which are necessarily efficient as well. This set can be interpreted as the hull of all feasible portfolios in the V,HDI-plane. This set turns out to be convex, as in ordinary financial portfolio applications.

We also show how, as the budget increases, these efficient portfolios move through the V,HDI-plane in a North-Easterly direction in most cases, following convex expansion paths for a given level of risk-aversion, indicating a more than proportional increase of V for a given increase in HDI. In some cases we find that these expansion paths are U-shaped, suggesting that there is a double dividend in expanding a low total budget in terms of HDI gained and V lost, or a 'double punishment' for decreasing an already low budget. We have also performed a sensitivity analysis that illustrates the working principles of the general approach and the importance of the selection of statistically significant model specifications, as statistically insignificant contribution parameters in one or more of the model equations in combination with risk-aversion provides a bias against inclusion of corresponding expenditures in the optimum development portfolio.

In most country/year combinations we have included in the analysis we find that actual HDI performance lags significantly behind the HDI range achievable through efficient spending of the actual available budget. Our approach enables us to indicate how existing budgets should then be reallocated and how much would be gained in terms of the accompanying HDI improvement.

Keywords Human Development Index, Public spending, Optimum Portfolio Theory

JEL classification H5, I, O2

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1. Introduction

In this article we present an approach to designing development policies that takes into account the intrinsic uncertainties surrounding the impact of individual development instruments on the development goals to be achieved. Instead of using a fully specified structural model that relates policy instruments to policy goals and targets, either directly or indirectly, we use a (linear) reduced form model that describes the statistical connection between instruments and targets. The benefits of this approach are obvious: the time necessary to specify and estimate the model is far less than for a fully specified structural model. The disadvantage is also obvious: the model is essentially a black box. However, as Friedman (1953) pointed out in the Fifties already, from a practical policy design point of view, the most important thing is that the black box actually works, i.e. that a significant link between targets and instruments does indeed exist and can be quantified to a sufficiently precise degree on the relevant policy range. Because the main aim of this article is to illustrate the working principles of our design approach, we will adopt Friedman's pragmatic stance.

In policy making, the statistical nature of the relation between targets and instruments is usually ignored, except for instances where one uses Monte-Carlo simulations. However, a bonus of explicitly acknowledging the statistical nature of the relation between instruments and targets is that it is easy to obtain the variance of some linear combination of targets (i.e. of a linear 'objective function') in terms of the variances in the measured contributions of the individual instruments to those targets. The Human Development Index (*HDI*) takes the form of a linear combination of such targets. Maximization of the *HDI* as the ultimate development target under some scarce resource constraint then requires the matrix of the expected values of the contribution coefficients of the instruments to the various sub-targets. The econometric estimation of these coefficients usually results in a situation where some non-zero (co-) variance of the estimates of the contribution coefficients remains. But then, picking some value of a particular instrument also implies picking a contribution of that instrument to the variance in the objective-function value. The latter is important, because policy makers tend to be risk-averse, and consequently, they could be expected to select from the collection of all feasible sets of instruments the one set that would generate the lowest variance for that particular objective function value. This particular set is efficient in the sense that it provides the highest positively valued result (the *HDI*) for a given value of a negatively valued result (the corresponding *HDI* variance).

The linearity of the *HDI* implies that its components are perfect substitutes for each-other, which is one of the criticisms raised against the *HDI*, see e.g. Sagar and Najam (1998) and section 2. Still, it has been widely accepted as a relevant measure of development, and so do we (also for pragmatic reasons). Given the existence of some resource constraint, this causes the exclusive selection of the instrument that would generate the highest contribution to the objective function per unit of the resource spent. With multiple resource constraints, the set of feasible instruments may become strictly convex, and a combination of different instruments may become optimal rather than just a single one. With risk-aversion, such a collection of instruments (further called instruments-portfolio, or IPF for short) may exist, regardless of the existence of multiple resource constraints, since the instruments become effectively imperfect substitutes because of the non-linearities involved in the contribution of each instrument to the variance in the objective function, or the portfolio-variance (as opposed to the single-instrument variance). Problems of this kind are familiar from financial optimum portfolio theory put forward by Markovitz (1952), and later extended by many others (Merton 1969; Samuelson, 1969) also in non-financial directions (Helfat, 1988; Seitz and Ellison, 1995; Awerbuch and Berger 2003; van Zon and Fuss, 2008; Fuss, 2008). The current article fits into the latter category, and is, as far as we know, the first application of the ideas of financial optimum portfolio theory to the design of development policies.

The article serves two purposes. The *first* is to show the working principles of the approach, also in a development context. To do this, we construct the simplest possible portfolio version of the development problem that contains all the components that are strictly necessary to define such a problem, no more, no less. The *second* purpose is to assess its potential relevance for the development problem. Therefore the components of the portfolio composition problem themselves are directly linked to concepts used in development policy decision making and implementation. The objective function, for instance, is translated into manageable modeling terms by taking it to be the maximization of a weighted sum of the *HDI* and its corresponding variance by means of controllable public spending on the targets directly contributing to the *HDI*. We specify this set-up for a large group of Sub-Saharan African (SSA) countries, asking ourselves how these countries should spend a given budget on the various targets, given the measured variances in the contribution coefficients, and given the existence of (different degrees of) risk aversion. It should be noted that limited data-availability for this group of SSA-countries has forced us to choose as simple a model specification as possible for purely pragmatic reasons. Still, the specification chosen works well in statistical terms (see also section 4).

The article is further organized as follows. Section 2 provides an overview of the different parts that make up our approach as well as the alterations/extensions we have made to be able to cover the design of efficient development portfolios. In section 3, we give a short overview of the data we have collected for our portfolio-exercise, while section 4 provides the estimation results. In section 5 we discuss the outcomes of our portfolio optimization problem, and investigate the efficiencies and inefficiencies involved in the development portfolios of individual SSA-countries as compared to the efficient portfolio frontier (further called *EPF*, for short). We try to assess how much of their inefficiencies are due to pure chance and how much due to inefficiencies in the allocation of resources. In section 6 we provide some concluding remarks.

2. Setting the Stage

2.1 General Outline

We feel that policy design should take into account that the impact of policies on the development process can not be known with complete certainty, and that some combinations of policy measures may generate less risk[1] than others. In fact, as people (and policy makers) are generally risk-averse, policy design should favor combinations of policies that generate the lowest risk for a given expected result at the aggregate level and for a given total budget, i.e. the policy portfolio should be efficient.

Under conditions of risk, the allocation of resources that have alternative uses, in our case public expenditures that could be directed towards alternative expenditure categories, is bound to not have the expected/desired effect, or at least not exactly. In addition, it may well be the case that realization 'errors' for different expenditure categories are correlated with each other. For example, an unexpectedly high effectiveness of education expenditures may make health and sanitation expenditures 'unexpectedly' more effective too. In Optimum Portfolio Theory, further called *OPT* for short, these correlations are taken into account from the outset, in defining efficient financial investment portfolios. We want to do the same when defining efficient development portfolios (*EDPs*).

We will show that the extension of *OPT* to cover the design of *EDPs* is relatively straight forward because of the correspondence between assets returns and *HDI* components on the one hand, and adding-up constraints on portfolio shares and those on expenditures on the *HDI* components on the other. The fundamental change in the *OPT* framework that is necessary for the design of *EDPs* is that of the addition of a (linear) system of simultaneous equations that describes how expenditures on the various *HDI*-components influence these components. We have estimated the parameters of that linear system (and their co-variances) for the SSA-countries in our sample. The co-variance matrix associated with the estimated contribution coefficients serves much the same function in our set-up as the co-variances between the individual asset rates of return in a pure *OPT* setting.

2.2 The Human Development Index

The recent report by the Commission on the Measurement of Economic Performance and Social Progress (Stiglitz et al., 2009) has made both policy makers and researchers acknowledge that measuring a country's development solely on the basis of GDP or GDP per capita is not sufficient, suggesting that a composite measure including different aspects such as income, health, education, environment, freedom, or equality would be more suitable. The biggest drawback to actually

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[1] In the literature, a distinction between risk and uncertainty is made. Risk is measurable through a known probability distribution, and uncertainty isn't. Cf. Knight (1921).

establishing such a composite measure is data availability, especially concerning the quality of education, health, and the environment on a macroeconomic level as well as inequality. Nonetheless, a multidimensional indicator for human development has been around for about 20 years in the form of the Human Development Index (*HDI*) developed by the United Nations Development Program (UNDP). The *HDI* was first published in the 1990 Human Development Report (UNDP, 1990). It measures "the average achievements in a country in three basic dimensions of human development: a long and healthy life, knowledge and a decent standard of living."[2] *HDI* data are available for more than 175 countries and regions. Even though the *HDI* was criticized from the very beginning regarding its incompleteness (e.g. measures of inequality were lacking), the way the index was calculated relative to the observed range of variation in the sample, but also the additive fashion in which the individual *HDI* components contributed to the aggregate index, the *HDI* has, since 1997, converged upon a final set of components, i.e. income, health and education (Klugmann et al., 2008). These components ensure that the *HDI* is a measure that can be characterized as 'universal', 'basic to life', and 'measurable' (Bérenger and Verdier-Chouchane, 2007). Meanwhile, other indicators addressing (some of) the shortcomings of the *HDI* have been made available as well.[3] Aggregate indicators that can be seen as complementary to the *HDI* are for example the Happy Planet Index (Abdallah et al., 2009), including happy life years and the ecological footprint, or the Human Poverty Index and the Gender Related Development Index developed by UNDP. However, for the purpose of illustrating our approach, but also because *HDI*-data are now readily available, we have opted for the *HDI* as our primary measure of development. This has the added bonus of us being able to rephrase the *HDI* in terms of the expected contribution coefficients of the estimated expenditure system, further explained in sections 2.4 and 4. Likewise, the variance in the *HDI* can be shown to depend directly on the co-variance matrix of these distribution coefficients (see Appendix A for more details).

2.3 Public Spending

Adopting a particular measure of development like the *HDI* as an adequate description of the state of development then logically implies that policies that are effective in raising the measured level of the *HDI* are to be preferred above policies that are less effective, *ceteris paribus*. Hence, the measurable impacts that alternative policies may have on the *HDI* may function as a screening device for the selection of policies, indeed for the design of a set of policies that may complement each other, i.e. a policy-portfolio. Development economists have dealt with the issue of designing effective development policies for quite some time. Indeed, there is a wide literature on the effect of aid on

[2] http://hdr.undp.org/en/statistics/indices/.
[3] For a short overview on other alternative indicators, see Berenger and Verdier-Chouchane (2007), p.1261.

development, see for example the special issue of the Review of Development Economics from 2009 (Mavrotas, 2009).

The focus of our attention in this article is on the design of internal spending policies, rather than on how external aid may affect development. This is in line with the views of African economists such as James Shikwati (Shikwati, 2006) or Dambisa Moyo (Moyo, 2009), who criticize monetary development aid and propose its complete removal since aid-recipients only become dependent and most of it ends up in the hands of corrupt elites (Grill, 2009). Rajan and Subramania (2005) even find that aid has a negative impact on growth. In addition to this, if aid is directly channeled to specific programs or projects, local policy makers do not necessarily have much of a say in where the aid flows go. In light of this discussion we will explore how African policy makers would be able to influence development through a better channeling of their public expenditures. Gomanee et al. (2005) take a step in that direction by examining the effect of aid on development through public expenditures.

There are three main approaches to analyzing public expenditure in developing countries. First, there is the more descriptive literature about how much the government spends in total, as a percentage of GDP, or, more specifically, on which sector; how public spending develops over time and how it compares across countries. These descriptions are mostly followed by other types of analysis, e.g. the analysis of the impacts of public spending on growth as in Fan and Rao (2003). Second, there is the analysis of public spending efficiency, i.e. how effective are, for example, health or education expenditures in determining health and education outcomes in different countries and at different times (e.g. Herrera and Pang, 2005; Herrera, 2007; Gupta et al., 1997; Jayasuriya and Wodon, 2008). Murillo-Zamorano (2004) surveys different efficiency frontier techniques (FDH and DEA) in this context. The third strand of literature stems from growth theory, where the effect of public spending on long-run economic growth is analyzed, e.g. Aschauer (1989), Barro (1990), Devarajan et al. (1996), or Fan and Rao (2003). Only some of these authors distinguish between different spending categories such as education or health. Furthermore, this literature measures the effects of government expenditure just on economic growth, which, by now, is an indicator considered to be too narrow a measure of a country's overall development.

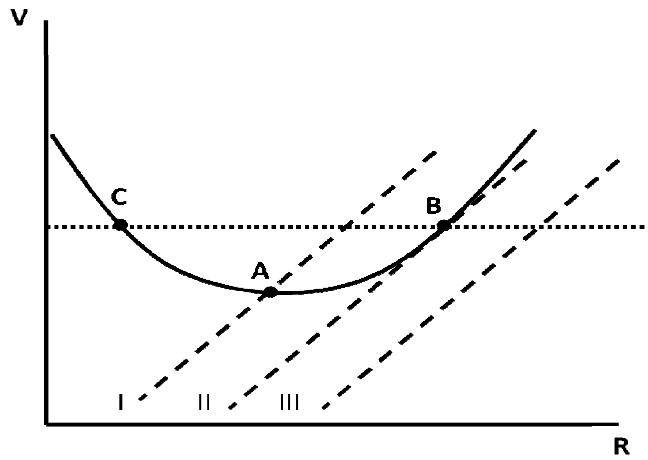
Obviously, the *EDP*-approach we develop in this article fits in with the second ('efficiency') strand of literature, but it does not stop with the measurement of inefficiencies. It also provides a direct indication as to how a reallocation of the public spending budget may improve the effectiveness of total spending in improving the Human Development Index. The only thing that is different is the notion of the efficiency of the public spending portfolio itself. The latter is defined not just in terms of the maximization of the returns/*HDI* for a given level of resources available (the 'traditional' efficiency concept), but also for a given level of the variance in the expected returns/*HDI* (the ‘extended’ efficiency concept from *OPT*): an *EDP* requires both ‘traditional’ and ‘extended’ efficiency of the allocation of resources.

2.4 Optimum Portfolio Theory and Efficient Development Portfolio Design

Optimum Portfolio Theory (*OPT*) was first described in Markovitz (1952). It refers to the problem of distributing a given budget over different financial assets, each of them with its own expected rate of return and a given co-variance matrix between the expected rates of return of these assets. A mathematical formulation of the static portfolio model is relatively straight forward, and we will use it as a template for the construction of our Efficient Development Portfolio (*EDP*) counterpart. In *OPT* an efficient portfolio maximizes the expected portfolio return for a given level of variance in that return, or, equivalently, minimizes the variance in the expected return for a given level of that return, by a suitable allocation of the budget over all alternatives. So an efficient portfolio exists without reference to risk-aversion. The notion of risk-aversion helps to define an optimum portfolio as the efficient portfolio for which an infinitesimal reallocation of the budget results in an infinitesimal small change in the positively valued expected portfolio return that is exactly offset by an infinitesimal change in the negatively valued corresponding portfolio variance. We will use the simplest possible portfolio valuation function (i.e. $\Theta(R,V)$) with a positive contribution of portfolio return (*R*) and a negative contribution of portfolio variance (*V*), i.e. $\Theta = R - \alpha V$, where $\alpha \geq 0$ is a constant parameter and is a measure of the degree of risk-aversion. Consequently, iso-valuation lines in the *V*,*R*-plane in Figure 1 are defined by: $V = R/\alpha - \overline{\Theta}/\alpha$, where $\overline{\Theta}$ represents a given and constant level of the valuation function. Note that the iso-valuation lines (labeled I, II, III) are straight and have a slope given by $1/\alpha$. The objective function value is increasing when going from I to II to III, since for a given value of *V* ‘going to the right’ in Figure 1 means an increase in R, hence an increase in the value of Θ.

Figure 1 shows the U-shaped efficient portfolio frontier, where the variance minimizing portfolio is represented by point A. This point corresponds to the highest possible degree of risk aversion, i.e. an infinitely high α implying a slope of the iso-valuation-lines equal to $1/\alpha \rightarrow 0$. The optimum portfolio, for some given positive and finite value of α is point B. Note that point C has the same *V*-value as B, but can never be an optimum portfolio, since B has higher return *R* than C. The upward sloping part of the U-shaped curve is therefore the economically relevant part of the curve. It follows moreover that for finite values of α the optimum portfolio given by point B will have both higher variance and a higher return than the minimum variance portfolio as given by point A. In addition to this, it should be noted that because of the convexity of the relevant part of the *EPF* the same increase in *R* tends to be associated with ever stronger increases in *V*.

Figure 1: The optimum portfolio selection problem



This OPT framework can serve as a template for the design of development policy. For the present article, we will be using a static framework, where decisions made in the present do not (explicitly) influence those that can be taken in the future. In such a static setting, policy design à la Friedman is relatively straightforward. The extension of the approach to an intertemporal setting is left for future research at this point.

Let *t* be the $T \times 1$ column-vector of *HDI* components (the policy targets), *y* be the $Y \times 1$ column-vector of per capita expenditures on Y expenditure categories and let *x* be the $X \times 1$ column-vector of exogenous variables of the expenditure system. Furthermore, *J* is the $T \times Y$ matrix of coefficients describing the unit-contributions of the expenditure categories to the *HDI* components, while *K* is the $T \times X$ matrix of coefficients linking the exogenous variables to the *HDI* components. Finally, *z'* is the transpose of *z* for any *z*, while $\hat{z}$ is the estimated/expected value of *z*, i.e. $\hat{z} = E(z)$, and ε^z is the associated error-vector/matrix (depending on the dimension(s) of z), i.e. $\varepsilon^z = z - \hat{z}$. Using this notation, we can write the expected *HDI* (denoted by $\hat{H}$) as:

$$\hat{H} = i'\hat{t}/T \tag{1}$$

where *i'* is the $1 \times T$ summation row-vector. Moreover, the vector of the expected values of the *HDI* components can be written as[4]:

[4] This can be regarded as the reduced form of a simplified structural model of African economies. A more detailed exposition concerning the choice of this model is given in section 4.

$$\hat{t} = \hat{J}\, y + \hat{K}\, x \tag{2}$$

The maximization problem we need to solve is:

$$\begin{aligned} \max_y \quad & \Theta = \hat{H} - \alpha \hat{V} \\ s.t. \quad & \hat{H} = i'\hat{t} / T \\ & \hat{V} = \hat{V}(y) \\ & \hat{t} = \hat{J}\, y + \hat{K}\, x \\ & B = i' Exp(y) \end{aligned} \tag{3}$$

where $\hat{V}$ is the expected variance in the *HDI* and where *B* is the per capita budget of government expenditures and $B = i' Exp(y) = \sum_{i=1}^{Y} \exp(y_i)$ is the budget constraint.[5] The only qualitative difference between this problem and a standard *OPT* problem is the presence of equation (2) as an additional constraint. However, equation (2) can essentially be removed through direct substitution of (2) into (1). This step redefines *H* (comparable in nature to the portfolio return *R* in the original *OPT* framework) in terms of the products of a number of matrices (*J* and *K*), the vector of decision variables (*y*) and the vector of exogenous variables (*x*), rather than just being the inner-product of the asset returns vector *r'* and the vector of budget shares as in a standard *OPT* problem. This makes the calculations more cumbersome, but the biggest problem, numerically speaking, is the non-linearity of the budget-constraint. The latter implies that the FOC's that implicitly describe the optimal solution to (3) become non-linear themselves. However, using Wolfram's © Mathematica software, we were able to calculate *y* numerically (and directly) as the solution to a set of simultaneous non-linear equations. The derivation of this set of non-linear equations is described in detail in Appendix A.

3. The Data

For our analysis we need data on the *HDI*-components, and on public expenditures by *HDI*-component. The *HDI* data stems from HDRO (2009) and is calculated as the arithmetical average of a health index (denoted by *lex* in Table 1) represented by life expectancy, a standard of living index (denoted by *gdp* in Table 1) represented by GDP per capita, and an education index (denoted by *edu* in Table 1), i.e. $HDI = (lex + edu + gdp)/3$. Using weights other than 1/3 does not substantially change the ranking of countries in accordance with their *HDI*-score, although, of course, it does change the

[5] The variance V is a relatively complicated expression in y that is derived in Appendix A. The non-linearity of the budget constraint arises because the coefficient matrices *J* and *K* have been econometrically estimated with the variables *y* measured as the natural logarithms of public expenditures on the various expenditure categories.

value of the index (Klugman et al., 2008). Note that the three components of the HDI, i.e. *edu, lex,* and *gdp*, are the elements of our vector of target variables *t*.

Data sources for government expenditures are the WHO (2009) and WDI (2009) databases. WHO (2009) provides data for per capita government expenditure on health in international PPP$ (our variable *geh*) and for general government expenditure on health as percentage of total government expenditure (for now called *percenth*). From these two we were able to calculate total government expenditure in international PPP$ as *get* = *geh/percenth*. WDI (2009) provides data on public spending on education as a percentage of government expenditure (*percentedu*). Per capita government expenditure on education then is *ged* = *get* × *percentedu*. Remaining government expenditures were simply calculated as the residual: *geg = get – geh – ged*.

For our computations we use 5-year averages to overcome frequent data gaps, as has for example been done in Adler et al. (2009). Thus we end up with values for 1995, 2000, and 2005 for about 30 SSA countries. The HDI shows some significant advances over these years, but, unfortunately, also a worsening of the index for some countries. The range of *HDI* values in 1995 was between 25% and 75%, which increased to values between 28% and 80% in 2005, while its mean remained at 47%. The highest HDI in our sample of SSA countries can be found in Mauritius and the lowest in Niger. Most countries have an HDI-score between 0.3 and 0.5.

Table 1: Descriptive statistics endogenous variables

Variable	Obs	Mean	Std. Dev.	Min	Max
hdi	19	0.47	0.12	0.28	0.80
lex	19	0.40	0.13	0.19	0.79
edu	19	0.55	0.20	0.18	0.83
gdp	19	0.47	0.15	0.32	0.79
get	19	747.80	1055.77	106.93	3264.92
geh	19	79.84	127.38	4.25	465.00
ged	19	137.88	204.76	14.98	666.89
geg	19	530.08	740.61	72.95	2335.20

Public spending per capita varies greatly between the SSA countries in our sample. Total government expenditures per capita (*get*) in 1995 are between 70 USD and 3200 USD. While the minimum steadily increases to more than 100 USD in 2005, the maximum decreases to 2900 USD in 2000 before increasing again to about 3200 USD per person in 2005. Even though South Africa has the highest total spending (*get*), it lags far behind Botswana in spending on education (*ged*) and health (*geh*). At the top end of public expenditures per capita are further Mauritius and Namibia. The Ethiopia and Niger have the lowest government expenditures per capita. While Ethiopia spends very little on all categories, Niger is doing comparably well on education and health spending. Burundi spends least on health (about 4USD per capita per year in all years).

Originally we employed *20* different exogenous variables which are commonly used as control variables when measuring development achievements of different countries (see, for example, the literature referenced in section 2). These exogenous variables can be grouped into different indicator categories: structural indicators, development indicators and dummies (former British (*GBCD*) or French (*FRCD*) colony dummy). Structural indicators, that were used here, are population density (*POPD*), urbanization rate (*URBR*), employment rate (*EMPR*), the share of agriculture (*EAGR*), industry (*EIND*), services (*ESER*), and trade (*TRAD*) in value added, and the crop production index (*CROP*). Development indicators mostly relate to health issues: immunization against measles (*IMMU*), malaria cases (*MALC*), HIV (*HIVR*) and tuberculosis (*TBPR*) prevalence rates, and access to improved water sources (*ATSW*) and to sanitation facilities (*ATSS*). We also included aid per capita (*AIDC*), but this turned out to be insignificant in all regression equations, as did several of the other variables, given that we included the three government expenditure categories. Descriptive statistics for those variables that were finally used in the estimation are presented in Table 2.

Table 2: Descriptive statistics of exogenous variables

Variable	Obs	Mean	Std. Dev.	Min	Max
gbcd	60	0.18	0.39	0.00	1.00
popd	60	94.42	138.29	2.01	612.13
urbr	60	32.98	14.51	7.22	60.20
empr	60	65.03	13.51	38.64	86.46
eind	60	26.83	14.38	9.96	82.00
eser	60	45.45	11.47	6.51	65.76
trad	60	75.52	38.32	24.32	200.76
hivr	60	5.71	6.60	0.05	24.88
tbpr	60	397.60	160.67	38.88	682.72
atss	60	34.75	20.76	5.00	94.00

4. Estimation Results

4.1 Estimated Model

Recall equation (2), i.e. $\hat{t} = \hat{J}\,y + \hat{K}\,x$. The vector *t* of policy targets consists of *T=3* variables, i.e. *lex*, *edu*, and *gdp*, while the vector *y* consists of *M=3* government spending strategies, i.e. government expenditures on health (*geh*), education (*ged*) and remaining (general) government expenditures (*geg*). Equation (2) can be thought of as the reduced form of a more general structural model, in which the target variables themselves are in part dependent on the values of the other target variables as given by: $\hat{t} = \hat{L}\,y + \hat{H}\,x + \hat{V}\,\hat{t}$. Obviously, the latter equation is equivalent to equation (2) when we define $\hat{J} = (I - \hat{V})^{-1}\hat{L}$ and $\hat{K} = (I - \hat{V})^{-1}\hat{H}$. For reasons of simplicity, we stick to equation (2) instead of the more general specification including the direct interaction between targets.[6]

4.2 Results and statistical assessment

Equation (2) describes the most general specification of our public expenditure system. Each equation could in principle have been estimated separately, but in our case we can not exclude the possibility that the errors associated with the equations are correlated, because we have had to restrict some of the parameter values in *J* and *K* to zero. In that case, it is no longer possible to use equation-by-equation OLS, and SUR is an appropriate technique.[7] We employed the SUR technique using Aitken's generalized least squares, which also provides the co-variances between the parameter estimates of all the model-parameters, also those across equations, which are needed to obtain the portfolio-variance as used in equation (A.6) in Appendix A. Using SUR ensures that we explicitly take into account the interdependencies between the equations.

Table 3 displays the estimation results for five different specifications of equation (2). Specifications 1 through 4 differ with respect to the specific coefficients of the three expenditure categories that are constrained to zero in the separate equations. While in specifications 1 and 2, both the coefficient of *lnged* (expenditure on education) and the coefficient of *lngeg* (remaining expenditures) are constrained to zero for the *lex*-equation (life expectancy index), only the coefficient of *lngeg* is constrained to zero in specifications 3 and 4. When including *lngeg* in the estimation, none of the coefficients corresponding to the expenditure categories were significant. This effect already becomes apparent in specifications 3 and 4, where neither of the coefficients of *lngeh* or *lnged* was significant at 10% (confidence level).

Specifications 2 and 3 do not restrict the coefficient of *lngeg* in the *edu* (education index) equation to zero. While the coefficient of *lngeh* is significant at 1% in all other specifications, it is only significant at 10% in specifications 2 and 3. The coefficient of *lnged* is significant at 10% in

[6] Strictly speaking, there is the possibility that GDP per capita has an influence on total government expenditures (through taxes, for example). To take this into account, we would need an additional constraint of the form: $y = W\,t + U\,x$, with government expenditures *y* depending on the target variables t, the exogenous variables x and possibly also other variables, resulting in a simultaneous system that could be estimated by three-stage least squares (3SLS) or the generalized methods of moments (GMM). Since we are interested in measuring the efficiency of the spending of a given budget, rather than explaining how that budget comes about, we disregard this possibility, and stick to equation (2).

[7] SUR stands for the technique of 'seemingly unrelated regression' which was developed by Zellner (1962). The SUR technique allows for the possibility that different equations that are using the same data and that are supposedly independent of each other, may still have errors that are correlated across the equations (Greene, 2003).

specification 4 only, when it is also included in the *lex* equation. Still, its value is between 0.03 and 0.04 in all specifications except for those not restricting *lngeg*. Also, Aikaike and Schwarz-Bayesian Information Criteria (AIC and BIC) are highest for specifications 2 and 3, so these two seem to be the least appropriate of the five specifications. AIC and BIC are third highest for specification 4, where neither coefficient of *lngeh* and *lnged* are significant in the *lex* equation.

Table 3: Estimation results

Specifications	Spec 1	Spec 2	Spec 3	Spec 4	Spec 5
lex					
lngeh	0.0205 *	0.0204 *	0.0005	0.0005	0.0287 **
lnged			0.0289	0.0290	
lngeg					
lnurbr	0.0578 **	0.0583 **	0.0620 **	0.0616 **	0.0616 **
lnpopd	0.0163 *	0.0165 *	0.0132	0.0130	0.0111
lnempr					0.0832
lneser	0.1002 ***	0.0999 ***	0.0588	0.0592	0.1086 ***
lntrad	0.0418	0.0418	0.0249	0.0249	0.0425 *
lntbpr	-0.0420 **	-0.0419 **	-0.0491 **	-0.0492 **	-0.0432 **
lnhivr	-0.0266 ***	-0.0266 ***	-0.0293 ***	-0.0293 ***	-0.0253 ***
gbcd	-0.0418	-0.0418	-0.0312	-0.0313	-0.0460 *
const	-0.1840	-0.1849	0.0336	0.0346	-0.5782
RMSE	0.0751	0.0751	0.0733	0.0734	0.0747
R-squared	0.6549	0.6549	0.6708	0.6707	0.6585
edu					
lngeh	0.0722 ***	0.0555 *	0.0543 *	0.0698 ***	0.0734 ***
lnged	0.0379	0.0253	0.0273	0.0401 *	0.0381
lngeg		0.0415	0.0401		
lneind	0.1375 ***	0.1202 ***	0.1211 ***	0.1380 ***	0.1384 ***
lnempr	0.2985 ***	0.3046 ***	0.3018 ***	0.2958 ***	0.3080 ***
lnatss	0.0685 ***	0.0616 **	0.0620 **	0.0685 ***	0.0676 ***
gbcd	0.0307	0.0387	0.0386	0.0310	0.0307
free					
const	-1.7606 ***	-1.8329 ***	-1.8212 ***	-1.7523 ***	-1.8051 ***
RMSE	0.1068	0.1061	0.1061	0.1068	0.1068
R-squared	0.6857	0.6900	0.6900	0.6858	0.6858
gdp					
lngeh	0.0431 ***	0.0439 ***	0.0413 ***	0.0405 ***	0.0444 ***
lnged					
lngeg	0.0797 ***	0.0786 ***	0.0819 ***	0.0830 ***	0.0780 ***
lnurbr	0.0328 **	0.0329 **	0.0323 **	0.0322 **	0.0332 **
lnpopd	0.0099 **	0.0099 **	0.0098 **	0.0098 **	0.0100 **
gbcd	-0.0180	-0.0181	-0.0176	-0.0174	-0.0182
const	-0.2513 ***	-0.2486 ***	-0.2557 ***	-0.2583 ***	-0.2477 ***
RMSE	0.0483	0.0483	0.0482	0.0482	0.0483
R-squared	0.8923	0.8922	0.8924	0.8925	0.8922
Number of obs.	60	60	60	60	60
D o F	22	23	24	23	23
AIC	-394.85	-393.43	-392.82	-394.26	-393.96
BIC	-348.78	-345.26	-342.55	-346.09	-345.79

Note. Significance levels: *** 1%, ** 5%, * 10%

Specification 5 differs from specification 1 in the control variables. It additionally includes *lnempr* in *lex*. Including the employment rate, which is not significant in *lex*, slightly improves the fit of the regression (measured by $\overline{R}^2$) and lowers the mean squared error (RMSE). The value of this coefficient is similar to those in specifications 1 and 4, but neither AIC nor BIC indicate that specification 4 outperforms specification 1, which therefore seems to be the most appropriate.

There is no indication of either heteroscedasticity or autocorrelation, so that specification 1 is valid and efficient. Still, as shown in our analysis in section 5.4 regarding the sensitivity of the final outcomes with respect to specifications spec1-spec5, we do have to keep in mind that the results do depend on the correct specification of the model. From now on we will concentrate on the results from specification 1, to show the applicability of the *EDP* method to developing development policies.

4.3 Results and impact of policy instruments on *HDI* components

As the signs of the coefficients of all types of government expenditures in Table 3 are positive, an increase in government spending improves the value of the individual *HDI* components. However, not all expenditure categories are equally important for all the *HDI* components. Only government expenditures on health seem to have an impact on the life expectancy index. These expenditures are also important for the other two indices (*edu* and *gdp*). Education expenditures have a lower impact (about 0.038) on the education index than health expenditures (about 0.072). Remaining government expenditures are not significant for *lex* or *edu*, but are important for the GDP index (the coefficient is positive and significant at 1%).

The index for life expectancy at birth is higher if urbanization rate (*lnurbr*), population density (*lnpopd*), employment rate (*lnempr*), share of services in total value added (*lneser*), and trade as percentage of total value added (*lntrad*) are higher, and if tuberculosis and HIV prevalence rate are lower. Former British colonies (*gbcd*) seem to have a lower life expectancy at birth index but better education index than former non-British colonies. The share of industry in total value added (*lneind*), the employment rate (*lnempr*), and the percentage of population with access to safe sanitation (*lnatss*) have a positive impact on the education index. The GDP index (*gdp*) is positively influenced by the degree of urbanization (*lnurbr*) and higher population density (*lnpopd*). Again, being a former British colony has a negative, though not very significant, impact.

5. Portfolio Application Results

5.1 Tracing the EPF

Given the estimates for the matrices *J* and *K*, including the cross-equation co-variances of the parameter estimates, the variance of the *HDI* (V) can be calculated as described in Appendix A, equation (A.6), and the *EDP* optimization problem, equation (A.7), can be solved for every country and for every year for which a full data-set is available. The *EPF* for a given budget for some country in some year can be (graphically) traced by calculating a sequence of optimum development portfolio's for a range of values of the risk-aversion parameter α. In our case, the range for all values of α is given by $\alpha = 1.5^x$ for all integer values of x from -19 to 9, implying that α increases by 50 percent for each unit increase in x.[8] We also varied the budget over a range as given by $B = 50 \cdot 2^a$ for all integer values of *a* in between 0 and 6 (cf. varying colors in Figures 2a and 2b). This budget range coincides with the observed range of variation for the actual budgets over the countries and years under consideration. The actual ETH 1995 (Ethiopia) per capita budget is only slightly higher than the budget low-bound of 50$ per capita, while MUS 2005 (Mauritius) is close to the budget high-bound of 3200$ per capita. In addition to this, we traced the *EPF* for the actually observed per capita budget (black curve). In the graphs, the variance (V) of an efficient development portfolio is plotted against its corresponding *HDI*-value (H).[9] The resulting EPF has a convex shape, as we would expect, given the resemblance of our EDP-composition-problem with an 'ordinary' OPF-problem. The results shown below include the actual *HDI* given by UNDP (represented by the vertical line), and the predicted *HDI* from our model (obtained by substituting equation (2) into (1)) and its corresponding variance for the actual budget (denoted by the position of the 'star'). Therefore, if the actual budget would be spent efficiently, the 'star' would need to be on the black EPF, save for the occurrence of random shocks in the contribution to the various targets of our model variables. Each point in the V,H-plane corresponds to a specific probability distribution, the higher the variance, the thicker the tails of the corresponding distribution and hence, the more likely to draw an HDI value that is further away from the expected value. Burkina Faso (Figure 2a), for example, has been 'unlucky', while Botswana (Figure 2b) has had a lucky draw as the actual *HDI* of the latter country exceeds the predicted *HDI*, and that of the former country falls below the predicted value. We will come back to this in more

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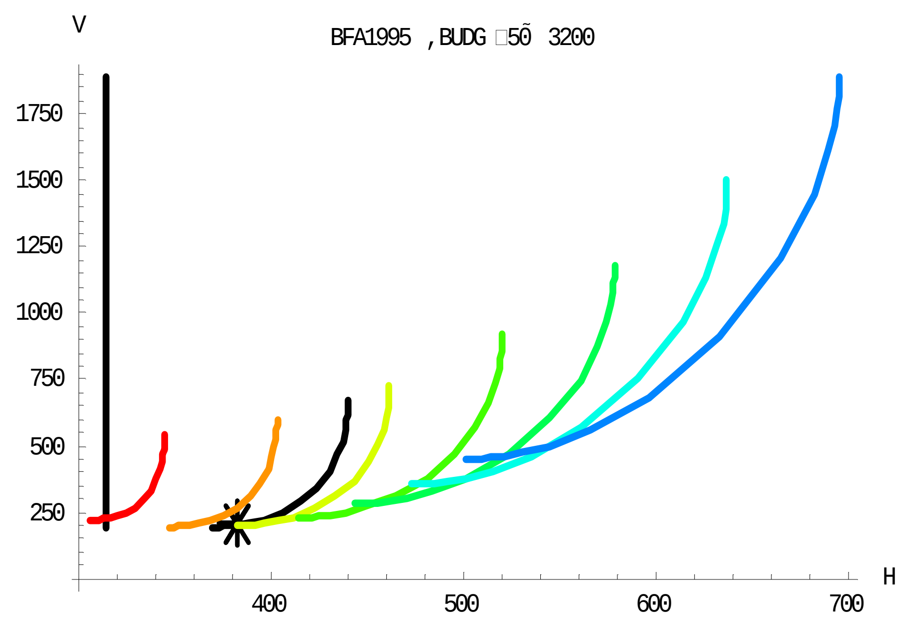
[8] We found no significant numerical trouble in calculating the OPF's for this wide range of values, but for even slightly wider ranges we did. For $\alpha = 1.5^{-20}$ LSO 2005 starts giving numerical trouble. Such trouble also arises for $\alpha \geq 1.5^{10}$. However, the remaining range for α is wide enough to be empirically relevant, as the implied slopes of the iso-valuation lines get close enough to zero and infinity.

[9] To avoid numerical problems, we have multiplied the K and J matrices by a factor 10^3, and the elements of the covariance matrix Ω by 10^6 (Var(1000x) = 1000²Var(x)) in order to retain a sufficient degree of numerical precision while tracing the *EPFs* for a wide range of α's. This has the effect of multiplying the expected *HDI* and its standard-deviation (being the square root of the variance) by a factor 10^3 as well.

detail in the next section that deals with the measurement of the impact of policy inefficiencies and pure chance on *HDI* scores.

The sequence of *EPFs* obtained by varying the budget over the budget-range of 50-3200 dollars per capita can essentially be classified using two different 'shape-classes'. First, there are *EPF* sequences that have (near) constant variance for low budgets, but then increasing variance for higher budgets (and correspondingly higher levels of *HDI*) for the highest value of α (i.e. the low-end of the *EPF*). An example that falls into this particular 'increasing' shape-class is Burkina Faso in 1995, see Figure 2a[10]. But sometimes it is the case that for the lowest budgets, the low-ends of the low budget-*EPFs* exceed those of higher budget *EPFs*. This suggests that in some cases, an expansion of the budget may give rise to a 'development double dividend' for risk-averse development policy makers: they could simultaneously improve their *HDI* score *and* reduce the riskiness of that score by increasing spending. In fact, in the example provided in Figure 2b, we see that the Botswana policy-makers have apparently been able to identify the size of the budget for which the double dividend becomes a trade-off between risk and return again, since an increase in the budget above the actual budget would tend to raise *HDI* but at the expense of a higher associated risk. The shape explained here is called 'U-shape' in the remainder of the article. [11]

Figure 2a: EPFs in Burkina Faso (1995)

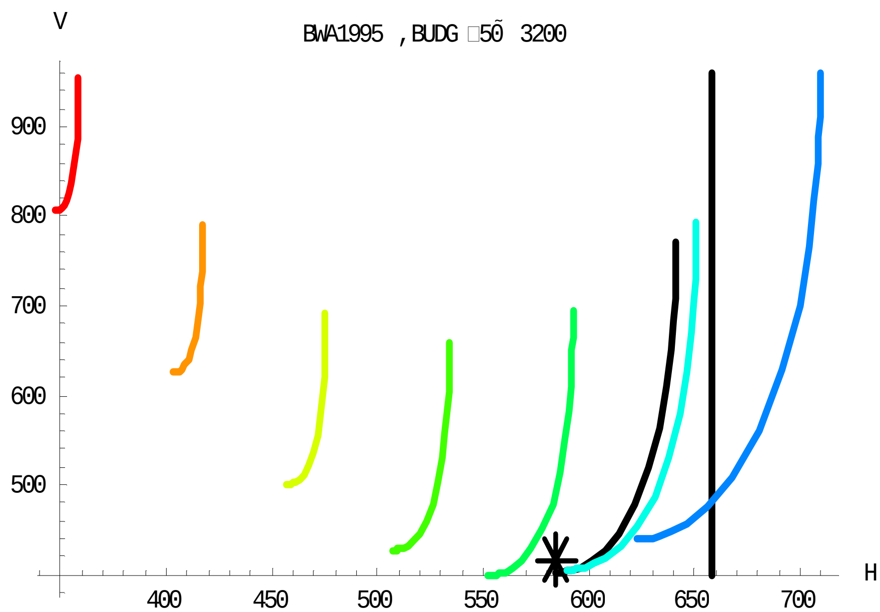


[10] One should keep in mind that the observations for 1995 are actually the 5 year averages over the years 1993-1997. The same holds, *mutatis mutandis*, for the observations for 2000 and 2005.

[11] Strictly speaking, it is possible that there is only one U-shaped class, of which the monotonically increasing shape class is a special case (i.e. numerically covering only the right-arm of the U-shape). For the moment this question is left for future research.

5 countries belong to the first group ('increasing'): BDI, BFA, ETH, MDG, and UGA;[12] and 24 countries to the second group ('u-shaped'): BEN, BWA, COG, CIV, CMR, COM, GHA, GMB, GNB, GNQ, LSO, MLI, MRT, MUS, MWI, NAM, NER, RWA, SEN, TCD, TGO, SWZ, ZAF, and ZMB. Of these countries, BEN, CMR, MLI and ZMB could definitely benefit from the double-dividend situation they are in by increasing their budget, since their 'black' *EPFs* are entirely to the left of the minimum in their respective U-shaped *EPF*-sequences. The EPFs corresponding to the actual budget of for example BWA, COG and CIV though are almost at the point of minimal possible variance.

Figure 2b: EPFs in Botswana (1995) with U-shape



5.2 Performance Measurement

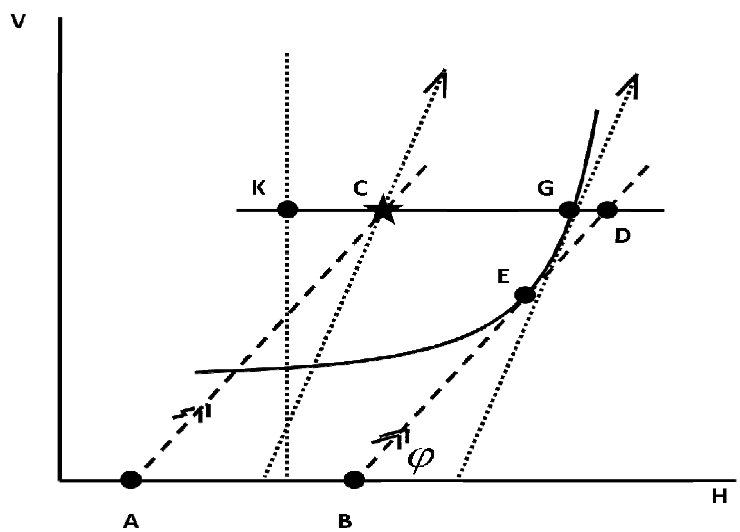
The *EPFs* that we have traced for all countries, all years and all budgets are all convex, as expected. However, the observed *HDI* does not necessarily intersect with the black *EPF* (i.e. the *EPF* achievable with the observed budget), nor is it necessarily the case that the 'star', i.e. the combination of predicted *HDI* and variance for the actual budget, lies on the black *EPF*. The deviation of the actual *HDI* from its expected value (as given by *HDI*-coordinate of the 'star') must be due to statistical flukes.[13] However, the difference between the *HDI*-coordinate of the 'star' and that of the point on the EPF

[12] See Appendix A3 for the definition of the country names and labels.

[13] Strictly speaking, the error could also be due to a misspecification of the model, which could make the country under observation differ from the 'representative' country covered by our estimated model. Obviously, we make the implicit assumption that our linear model is completely and correctly specified. Also using estimation specifications 2 to 5 for this analysis we find that the resulting relative positions of the black EPF, the predicted HDI (the star), and the actual HDI (black vertical line) do not change in the vast majority of cases. The only exceptions to this are BDI1995, GNQ1995, and ZMB 1995, where the predicted HDI is very close to the actual HDI for all specifications.

with the same V-coordinate must be due to inefficiencies in the allocation of the public development budget. This non-stochastic part of the extended efficiency losses associated with such inefficiency can be removed by changing the budget allocation such that the 'star' will be on the (black) *EPF*. Recall that the extended efficiency is the objective function value Θ, i.e. the positively valued HDI minus its variance multiplied by α. In this section we will measure the minimum amount by which extended efficiency could be improved for a given budget, by efficiently spending that budget.

Figure 3. Extended Efficiency Measurements



In Figure 3, point C (the 'star') depicts the V,H-coordinates that correspond with the expected values associated with the actual budget allocation, while the dotted vertical through point K corresponds with the actual realisation of the HDI. The EPF is the convex curve through points E and G. Point E is some point on the EPF that would be chosen by a person with an α equal to the co-tangent of the angle φ. This is because the line tangent to the convex *EPF* in point E is an iso-valuation line, given by $\Theta^E = H^E - \alpha^E V^E$, implying that $V^E = H^E / \alpha^E - \Theta^E / \alpha^E$ (the superscript E here refers to point E on the *EPF*). Note that this iso-valuation line represents the highest value of the objective function that a person with $\alpha = \alpha^E$ can achieve. Point E would represent the optimum portfolio for that person. That person would value point C using the same α^E, and obtain an objective function value given by the H-coordinate of point A on the horizontal axis.[14] But since C and A are on the same iso-valuation line, the objective function value in C is also equal to the *HDI* coordinate of point A. The same goes, *mutatis mutandis*, for points B and D.

[14] On the horizontal axis, the V-coordinate is zero, so the objective function value associated with some point on the horizontal axis must be equal to the *HDI*-coordinate.

In order to measure the potential size of extended efficiency improvements due to more efficient spending, we would like to know the minimum improvement that people could achieve by moving from a point like C to some point on the *EPF*, say a point like E, i.e. we are looking for (a person with) a degree of risk-aversion α^E that implicitly defines point E such that the extended efficiency gain ($\Delta\Theta$) from the move from C to E would be minimal. Hence, having any other degree of risk aversion results in an even larger gain, implying that everybody will at least be as well off as the person with risk-aversion α^E.

The extended efficiency gain from a move from C to E is given by:

$$\Delta\Theta = \Theta^E - \Theta^C = H^E - H^C - \alpha^E (V^E - V^C) \qquad (4)$$

A movement along the *EPF* can be interpreted as a change in V that comes from a change in H that in turn is caused by a change in α^E. But then, minimisation of (4) with respect to α^E implies:

$$\frac{\partial \Delta\Theta}{\partial \alpha^E} = \frac{\partial H^E}{\partial \alpha^E} - (V^E - V^C) - \alpha^E \frac{\partial V^E}{\partial H^E} \frac{\partial H^E}{\partial \alpha^E} = 0 \qquad (5)$$

Since $\partial V^E / \partial H^E$ is the slope of the EPF in point E, we must have that $\partial V^E / \partial H^E = 1/\alpha^E$. But then (5) implies that $V^E = V^C$, i.e. the point on the *EPF* that represents the smallest improvement of the objective function relative to point C must have the same V-coordinate as point C. Hence, the point we are looking for must be point G [15], and the extended efficiency gain involved in moving from C to G is given by the length of the line-segment in between those two points and is measured in *HDI*-units. Note, however, that the corresponding extended efficiency *levels* (in equivalent *HDI*-terms) are given by the *HDI* coordinates of the points of intersection of the parallel dotted lines (with single arrow heads) through C and G with the horizontal axis. [16]

Unfortunately, the extended efficiency function that we use does not have a 'natural' point zero. People with high degrees of risk-aversion may be faced with negative values of the objective

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[15] The second derivative $\partial^2 \Delta\Theta / \partial \alpha^{E^2} = -\partial V^E / \partial H^E \cdot \partial H^E / \partial \alpha^E > 0$ since a higher degree of risk-aversion would lower both H and V, i.e. $\partial H^E / \partial \alpha^E < 0$. The extended efficiency gain is therefore indeed minimised when moving from C to G, since the second derivative is positive.

[16] Obviously, since the dotted lines with single arrows in Figure 3 are parallel, the *HDI*-difference between points C and G is exactly equal to the *HDI* difference between points A and B. The latter difference, however, represents the extended efficiency difference between points A and B (since the variance component is zero in both points A and B), and so the *HDI*-difference between points C and G is also equal to the extended efficiency difference between these points, we can therefore interchange extended efficiency and *HDI* differences, as we have done in Figure 3.

function and be perfectly happy with that. In that case relative changes in the objective function value make little sense, even though absolute changes still do. We will therefore provide information in terms of absolute changes.

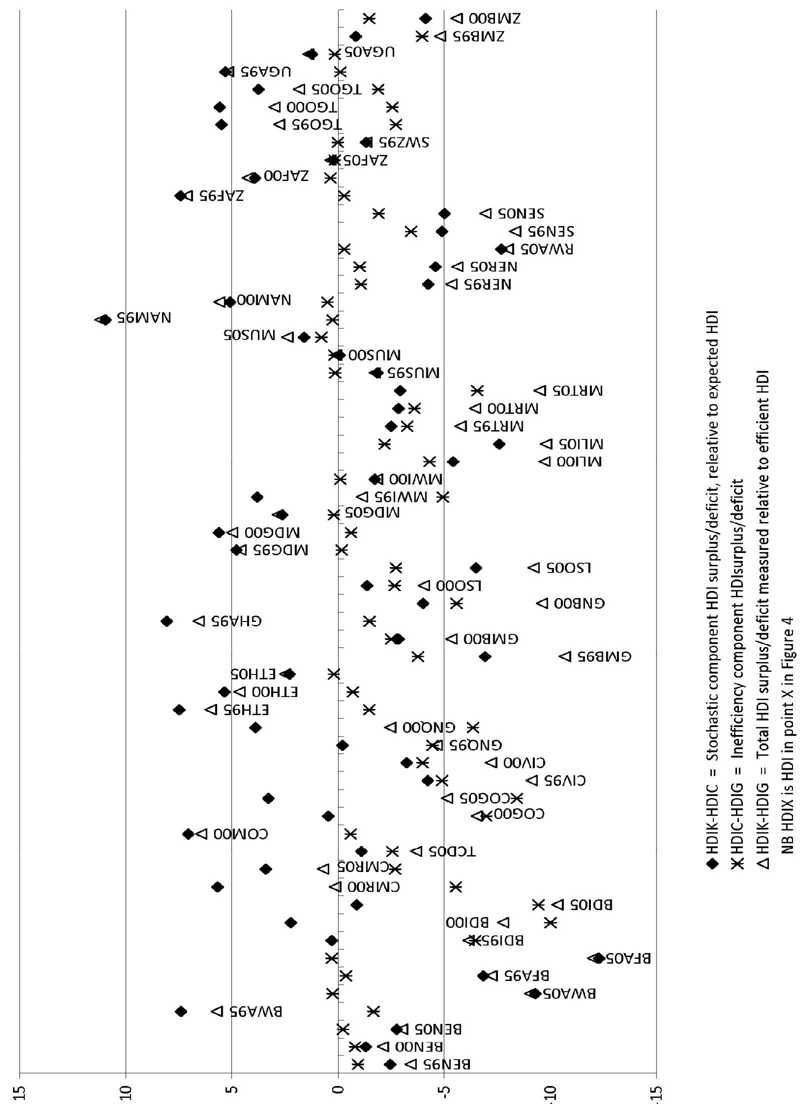
The extended efficiency contributions of both the transitory and the structural components are shown in Figure 4 for all country/year combinations for which a full data-set is available. The calculations are based on Figure 3, where point G is the point of reference, and the total extended efficiency surplus consists of two components, since $\Theta^K - \Theta^G = \{\Theta^K - \Theta^C\} + \{\Theta^C - \Theta^G\}$. The first bracketed term represents the extended efficiency surplus over the expected value of extended efficiency, given the way in which the budget was spent in actual fact (if positive, we were lucky). The second bracketed term represents the extended efficiency surplus of the way in which the actual budget was spent over the extended efficiency associated with an efficient spending of the same budget. Obviously, one would expect the latter surplus to be negative, or at most equal to zero if the actual budget allocation would have proved to be efficient, and this is what we can observe in Figure 4[17], where the extended efficiency changes mentioned above have been expressed in equivalent *HDI* changes (see Figure 3 and note 16).

5.3 Allocation inefficiencies

Figure 4 below has some striking features. First of all, allocation inefficiencies are relatively important for Burundi (BDI), and consistently so. At the same time, the contribution of pure chance has been of limited size, so that the negative extended efficiency effects for Burundi are mainly structural in nature. However, these extended efficiency deficits could be fixed, by adopting more efficient spending programs. By contrast, Ethiopia (ETH) has consistently been lucky, although the contribution of pure luck has fallen and that of efficient resource allocation has risen over time. Other countries that have seriously suffered from bad luck, which is defined here as a transitory loss of more than 5 percentage points are BWA2005, BFA1995, BFA2005, GMB1995, LSO2005, MLI2000,2005, RWA2005, SEN2005 whereas such countries as BWA1995, CMR2000,2005, GHA1995, MDG2000, NAM1995,2000, ZAF1995, but also TOG1995-2000 and UGA1995 have been lucky using the same measure.

[17] There are some minor positive deviations, however, that are due to the fact that we obtain the value of α^G numerically using Mathematica's Interpolation function that represents the black EPF as an interpolation of the outcomes of the efficient combinations of V and H that we have calculated for the range of α's discussed above. We then invert this interpolated function to obtain the α corresponding to a certain value of the variance V. This variance V is the value that we can calculate using equation (A.6) for the observed budget allocation. The resulting value of α is then used to evaluate the implied objective function value for that interpolated value of V, as we also have obtained *HDI* along the EPF as an interpolated function of α.

Figure 4. Extended efficiency surpluses and deficits



A major overall result is that the contribution of pure chance or 'fate' is generally of considerable importance. However, the bonus of experiencing inefficiencies instead of being confronted with fate is that the former can be tackled, whereas, in principle, fate can not. Nonetheless, we have tried to correlate the various extended efficiency deviations from Figure 4 (but now scaled by the budget in order to take differences in budget-sizes and their impact on *HDI* scores into account) with some governance indicators, the hypothesis being that both fate and bad allocation decisions might have something to do with the lack of quality of governance. To this end, we calculated the correlations (K-tau and Spearman because of their small sample properties) between extended efficiency deviations and different governance indicators. The latter are the Freedom house political rights (FHPR) and civil liberty (FHCL) index and a combination of these two, called FREE.[18]

Table 4. Extended efficiency surplus and Governance correlations

	K-tau			Spearman		
	FHPR	**FHCL**	**FREE**	**FHPR**	**FHCL**	**FREE**
OBJ(K) - OBJ(G)	0.074	0.123	-0.117	0.136	0.204	-0.182
OBJ(C) - OBJ(G)	-0.317***	-0.371***	0.306***	-0.482***	-0.555***	0.483***
OBJ(K) - OBJ(C)	-0.072	-0.050	0.024	-0.109	-0.079	0.054

Note. Significance levels: *** 1%, ** 5%, * 10%

OBJ(K)-OBJ(G) = total extended surplus (+/-), measured relative to efficient point G

OBJ(C)-OBJ(G) = extended efficiency surplus (+/-) due to efficient/inefficient budget allocation

OBJ(K)-OBJ(C) = extended efficiency surplus (+/-) due to good/bad luck, measured relative to point G

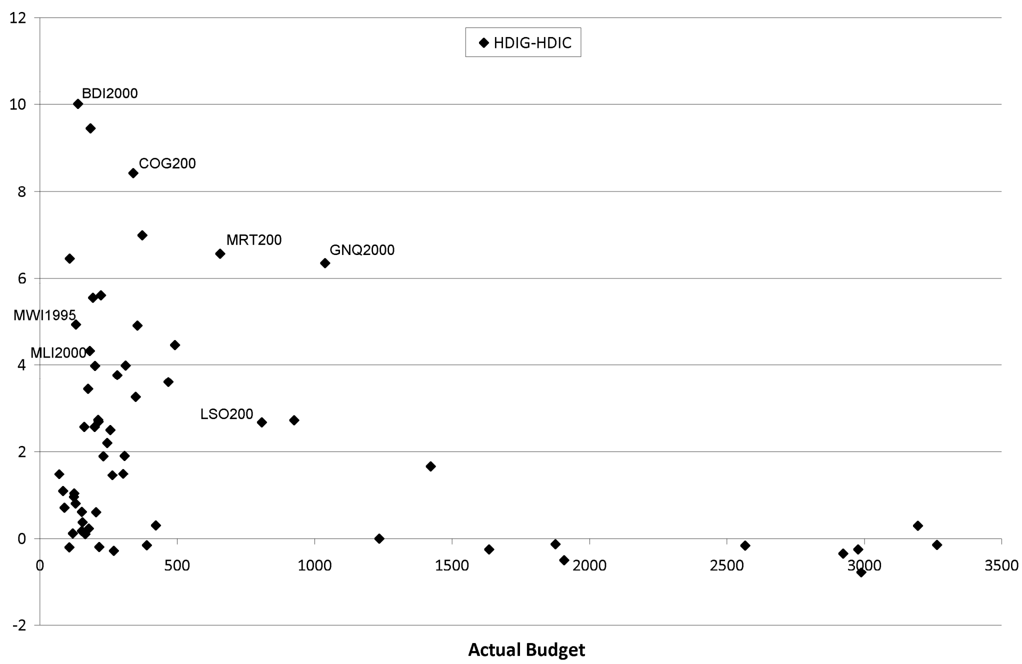
The correlations between these governance indicators and the partial and total deviations are shown in Table 4. It becomes immediately clear that a relatively high extended efficiency surplus due to efficient spending is positively correlated with good governance, indicated by the highly significant correlations in the second row of Table 4. These correlations of the surplus and governance are negative for FHPR and FHCL (where high values indicate bad governance), and positive for FREE (where low values indicate bad governance). The correlations of total extended efficiency surplus with the governance indicators, displayed in the first row, are of the same sign, but no longer significant. This underlines both the practical importance and the unpredictability of the contribution of fate to the total extended efficiency surplus. Nonetheless, even though the extended efficiency contribution of inefficiencies in government spending is relatively limited, these inefficiencies are heavily correlated with governance indicators, suggesting that extended efficiency improves as the quality of governance increases.

In order to establish the practical importance of reducing inefficiencies in government spending, the most important information from Figure 4, i.e. the potential (minimum) improvement in extended efficiency due to a move from point C to point G in Figure 3, has been presented again in Figure 5. We see that countries like COG 2005 and MRT 2005 would benefit greatly from more efficient government spending. This holds a fortiori for BDI 2000 in which the potential 10 percentage

[18] Both FHPR and FHCL are measured on a scale from 1 to 7, with 1 representing the highest degree of freedom and 7 the lowest. FREE on the other hand is equal to 1, if the average of FHPR and FHCL is lower than 3.5 (i.e. a country is relatively free), equal to 0.5 for an average between 3.0 and 5.5, and 0 for an average higher than 5.5.

point increase in *HDI* represents a proportional increase of 30 percent relative to the expected *HDI*, which is extremely low to start with for BDI 2000, i.e. slightly above 30 percent. For some other countries too, more efficient government spending can bring about relative changes in those countries' *HDI* of more than 10 percent. Examples are MWI 1995, MLI 2000, GNQ 2000 and LSO 2000. Given that the average HDI of the sample countries is 0.47, for most countries the potential increase in *HDI* is limited to less than 10 percent of the expected *HDI*. Nonetheless, an increase of even a few percentage points in the *HDI* of a country may be of considerable practical importance for the people involved, as it could make the difference between being just alive and being able to make a living.

Figure 5. Possible improvement in HDI (in % points) with efficient spending



The question now is what the removal of inefficiencies requires in terms of the reallocation of the government budget. To answer this question, we have calculated the percentage point differences between the budget distributions in points G and point K in Figure 3, for each country/year combination for which we have a complete data-set. In order to be able to assess the practical significance of the changes in the budget allocation thus calculated, we also present the actual budget allocation as a radar plot in Figure 6, to give an impression of the size of the numbers involved and the variation in these numbers over countries and over time. Figure 7 contains the differences between the efficient budget distribution and the actual budget distribution over the three categories, i.e. the percentage point change in the budget allocation that would be needed to make the development portfolio efficient and to realize the percentage point *HDI* gains shown in Figure 5.

Figure 6. Actual budget distribution (% shares)

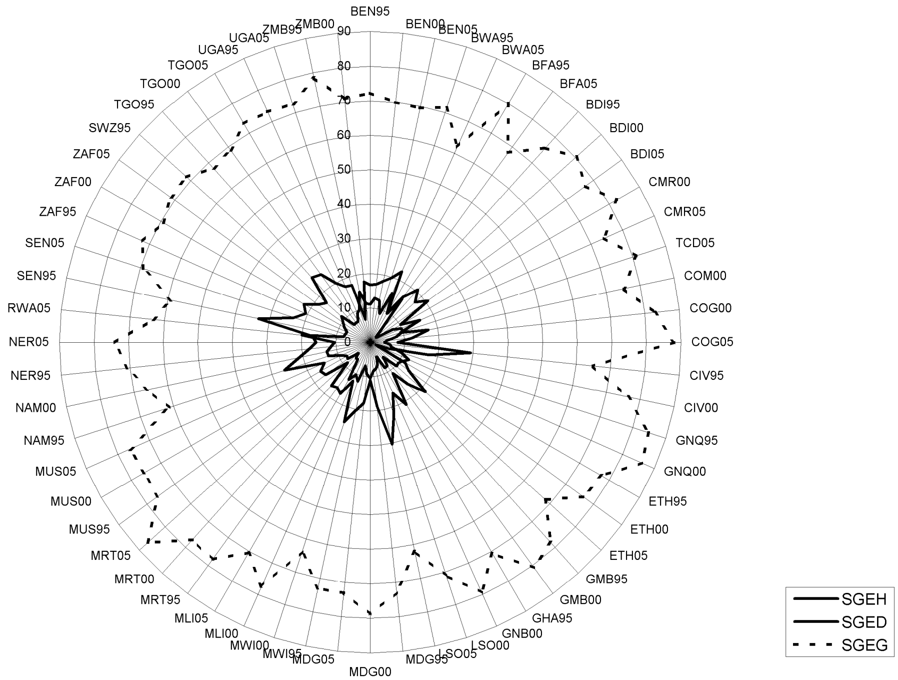
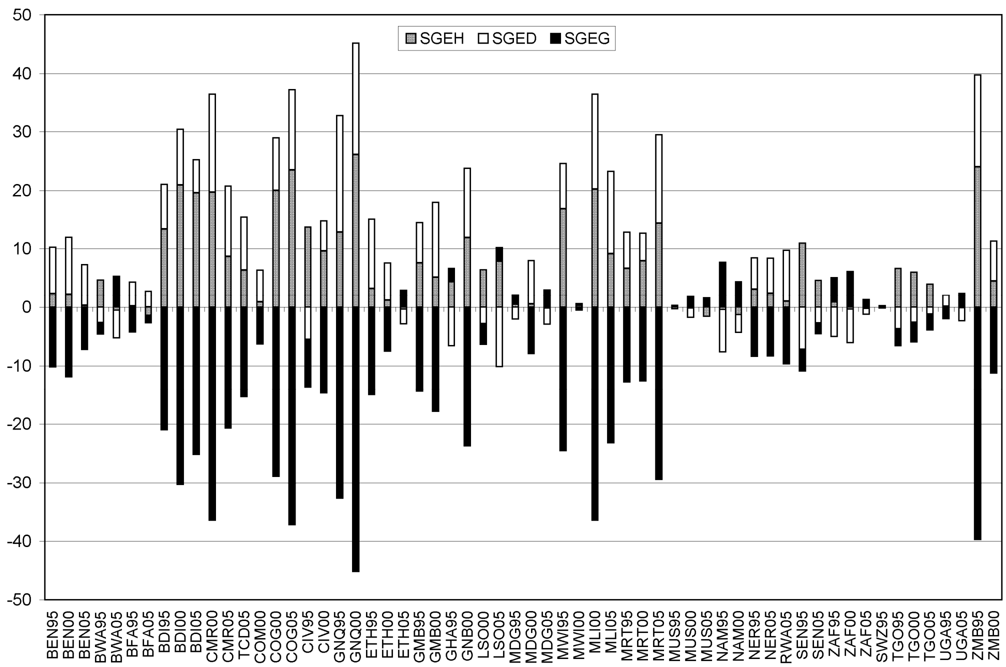


Figure 6 shows that the share of general government spending is relatively high, and relatively stable at around 70 to 80 percent of the total budget, with just a few exceptions in which the share exceeds 80 percent (like BFA1995, BDI2000, CMR2000, TCD2005, COG2000,2005, GNQ1995,2000 and MRT2005) and a few more in which the share is below 70 percent. This generally leaves little to distribute over health and education expenditures. The share of education expenditures (labeled SGED) takes roughly 20 percent of the budget, while health expenditures (labeled SGEH) take the remainder, i.e. only about 5 to 10 percent. It should be noted that the countries that are below average general government spenders spend relatively more on education. The variation in education and health expenditure shares between countries is larger than the variation in general government expenditure shares.

Looking at Figure 7, we can make an important observation. In the vast majority of cases, extended efficiency could be improved by increasing the budget spending shares of education and health. In cases where the budget reallocation is of considerable size we see that most of the drop in general government expenditures goes to health expenditures and less to education, thus effectively making the distribution of the budget more even among the three categories. There are very few countries where general government budget expansions are wanted, and if so, the increase in the share of general government expenditures amounts to just a few percentage points. These countries are the ones that were already spending their budgets relatively efficiently (see also Figure 4). However, there are quite a few countries for which large reductions (20% or more) in the share of general government expenditures are wanted, or, equivalently, equally large increases in the joint share of expenditures on health and education are/would have been required. These countries are BDI1995-2005, COG2000-2005, GNB1995-2000, MWI1995, MRT2005, NGA1995, ZMB1995.

Figure 7. Percentage point differences efficient and actual budget distribution

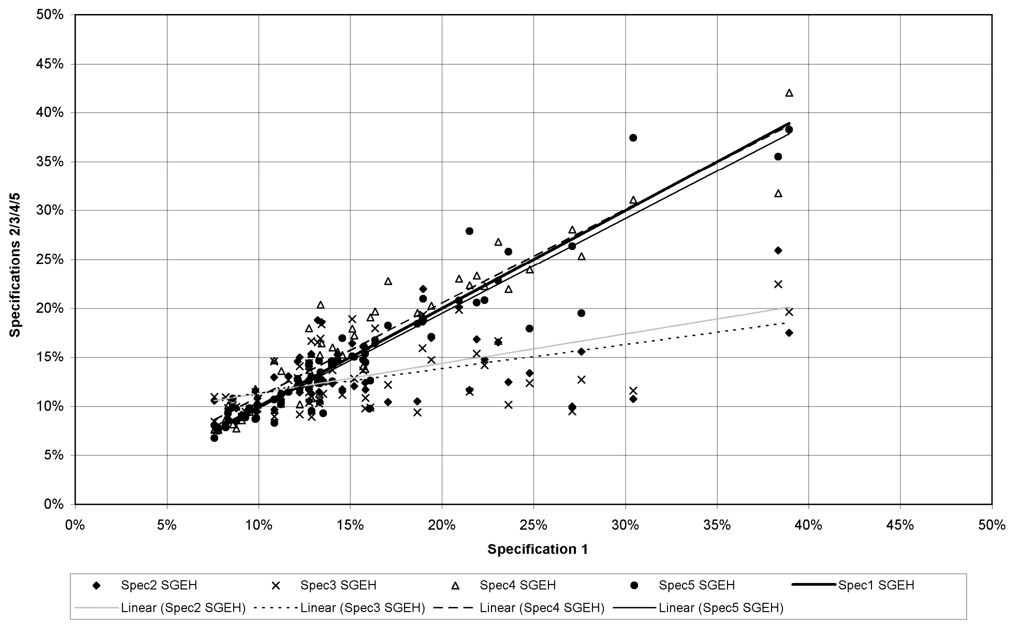


5.4 Sensitivity analysis

In Figures 8a-8c we present the plots of the expenditure shares in the various specifications in Table 3 for each country/year combination against each corresponding country year combination in our preferred specification 1. The thick black line in each Figure represents a reference line as it is associated with specification 1 against specification 1, hence the unit-slope.

When plotting the *EPF's* for the different specifications in Table 3, we found that the general shape and position of these *EPF's* in *V,H*-space did not change much (not shown here). More variation could be observed in the underlying expenditure shares, even though specifications 5 and 1 are remarkably similar, indicating that the employment rate impact (the only 'real difference' between specifications 1 and 5), including the contribution of its co-variance does not do much. Fairly similar are the results of specification 1 and 4. Still, specification 4 involves a structural three percentage point change in the share of education expenditures at the expense of general expenditures. This is because education now also has an impact on health, so there is a double-dividend to education expenditures in specification 4 as compared to specification 1.

Figure 8a. Health expenditure sensitivity results



There is a striking difference between specifications 2 and 3 on the one hand, and specification 1 on the other. The cause of the difference is the relatively large positive coefficient of *lngeg* in the *edu* equation in combination with that coefficient being insignificant, i.e. showing a relatively large (co-)variance. Both aspects are important, because on the one hand the double dividend of general expenditures now raises the share of the latter, while on the other hand the increased contribution of *lngeg* to portfolio variance introduces a motive to move out of these expenditures, and more so if these expenditures are relatively high raising the other expenditure shares in the process. This has the effect of reducing the slopes of the lines reflecting the correlations between specifications 2 and 3 on the one hand and specification 1 on the other. Still, according to the econometric model, *lngeg* is not significant in *edu*, and even though the adjusted R-squared suggest a better fit of either specifications 2 or 3, the Aikaike and Bayesian-Schwarz Information Criteria are higher for these two specifications compared to the other three specifications, suggesting that specifications 1, 4, and 5 are to be preferred over specifications 2 and 3 on purely statistical grounds.

Figure 8b. Education expenditure sensitivity results

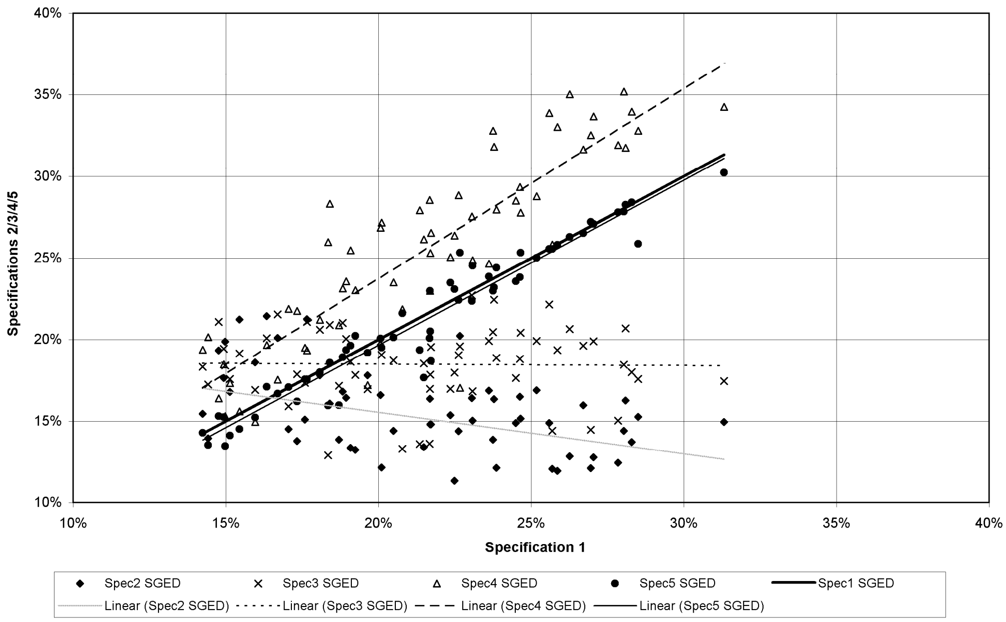
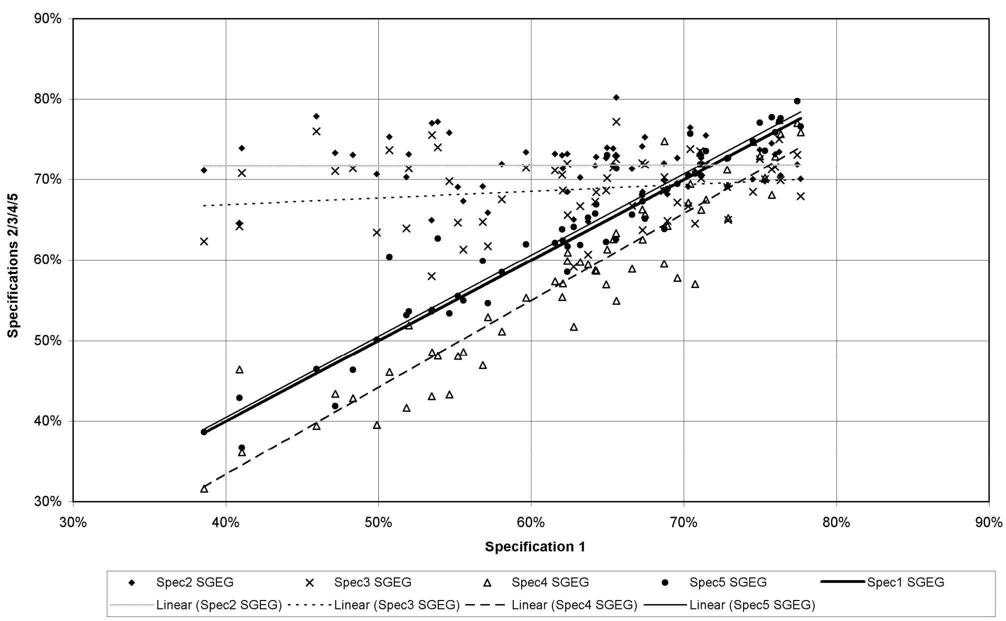


Figure 8c. General government expenditure sensitivity results



6. Summary and Conclusion

In this article we have presented the outlines of a method that enables the assessment of the efficiency by which development is promoted in SSA countries through local government spending.

We describe the process of development through its associated impact on the Human Development Index (*HDI*). A sensitivity analysis concerning the widely criticized linear aggregation scheme with equal weights for the three indexes is left for future research. The purpose of the present exercise is to show the application possibilities of the method in this field.

To this end, we estimate a simple cross SSA country simultaneous system of equations that links government expenditures on the three *HDI* components to the scores on the three *HDI* components in a setting that allows for exogenous differences between countries that would determine the general setting in which the underlying development processes are taking place, and that define in part the effectiveness of government spending in raising the *HDI* components. By estimating this system of equations, we obtain measures of the risk associated with using the three spending instruments. We make the assumption that policy-makers are risk-averse, implying that they would prefer a policy outcome of spending a given budget on the three *HDI* components with a particular expected value of the *HDI* outcome and a corresponding variance of that outcome above a policy with the same expected *HDI* but a higher variance of that outcome. This setting resembles the one known from Optimum Portfolio Theory (OPT), but it extends the OPT setting by allowing for multiple constraint on the use of (policy-) instruments. In our case, the simultaneous estimation model forms an additional set of constraints next to the government budget adding-up constraint and the one that links the value of the *HDI* to its components.

In our setting, an efficient development portfolio is a distribution of the government budget that minimizes the variance of the *HDI* for a given expected value of the *HDI*. We find that the *EPF's* can be represented as convex upward sloping graphs in the variance, *HDI*-plane. Using this setting, we are able to define a point on the *EPF* of each SSA country that marks the minimum increase in extended efficiency (a measure that includes both the expected *HDI* and its variance) that could be realized by an efficient spending of the government budget. We then show how the actual performance of each SSA country can be split into a transitory component brought upon these countries by good or bad luck, and a structural component that is linked to good/bad budget allocation decision making. We show that the good/bad luck component is of considerable importance. However, to some extent it may be the case that what we have called 'luck', is actually a 'measure of our ignorance'. For now we have to leave the potential reduction of that ignorance for future research.

The structural extended efficiency loss component is correlated with a number of governance indicators pointing to the 'rule of thumb' that good governance is associated with efficient budget spending and bad governance with inefficient spending. We also show that the changes in the composition of the budget for countries that are spending inefficiently are considerable, i.e. expenditures on health and education should be increased by 20 percentage points or more, whereas in most cases expenditures on health and education are of the order of 20 percent to start with. Hence, efficient reallocation requires a doubling of the health and education budget, and a more equal distribution of the overall budget over the three expenditure categories. For some countries, general government expenditures need to be raised, but only by a small amount, and the other categories need to be adjusted accordingly. This is the case only for countries that are already spending relatively efficiently.

The sensitivity analysis we performed led to the conclusion that the shape and position of the EPF as well as the predicted HDI are robust to different estimation specifications, while the necessary budget changes to get to the EPF show more variability. Using specifications with insignificant parameter contributions by some expenditure category does introduce a bias against using that category through its relatively high (co-) variance in combination with risk-aversion. We conclude that estimating the model correctly is essential for applying the method and interpreting the results.

Appendix A. Derivation of the EDP FOC's

In this appendix we show how the FOC's can be derived that implicitly describe the solution to the maximization problem provided in (3). First, it should be noted that errors in *H* can only be caused by errors in *t*. Hence, from (1) it follows that:

$$\varepsilon^H = i'\varepsilon^t / T \qquad \text{(A.1)}$$

Moreover, assuming that we know both y and x with absolute certainty[19], it follows from (2) that:

$$\varepsilon^t = t - \hat{t} = (J\,y + K\,x) - (\hat{J}\,y - \hat{K}\,x) = (J - \hat{J})\,y + (K - \hat{K})\,x = \varepsilon^J y + \varepsilon^K x \qquad \text{(A.2)}$$

Note that (A.2) assumes that there are no measurement errors in *x* or implementation errors in *y* nor any other (forecast) errors. Using (A.1), the variance in the *HDI* is given by:

$$V = E(\varepsilon^H \varepsilon^{H'}) = E(i'\varepsilon^t \varepsilon^{t'} i / T^2) = i'E(\varepsilon^t \varepsilon^{t'})i / T^2 = \sum_{i=1}^{T}\sum_{j=1}^{T} E(\varepsilon_i^t \varepsilon_j^t) / T^2 \qquad \text{(A.3)}$$

with $\varepsilon^t \cdot \varepsilon^{t'} = \begin{pmatrix} \varepsilon_1^t\varepsilon_1^t & \varepsilon_1^t\varepsilon_2^t & \varepsilon_1^t\varepsilon_3^t \\ \varepsilon_2^t\varepsilon_1^t & \varepsilon_2^t\varepsilon_2^t & \varepsilon_2^t\varepsilon_3^t \\ \varepsilon_3^t\varepsilon_1^t & \varepsilon_3^t\varepsilon_2^t & \varepsilon_3^t\varepsilon_3^t \end{pmatrix}$.

In equation (A.3) ε_i^t is the i-th element in the error-vector ε^t, i.e. it represents the error (i.e. the deviation from expectation) in target variable *i*. Using equation (A.2), it follows that:

$$\varepsilon_i^t = \sum_{k=1}^{T} \varepsilon_{i,k}^J y_k + \sum_{l=1}^{X} \varepsilon_{i,l}^K x_l \qquad \text{(A.4)}$$

Substituting (A.4) into (A.3), we get:

$$\begin{aligned} E(\varepsilon_i^t \cdot \varepsilon_j^t) = {} & \sum_{k=1}^{Y} y_k \sum_{m=1}^{Y} E(\varepsilon_{i,k}^J \varepsilon_{j,m}^J) y_m + \sum_{k=1}^{Y} y_k \sum_{m=1}^{X} E(\varepsilon_{i,k}^J \varepsilon_{j,m}^K) x_m + \\ & \sum_{k=1}^{X} x_k \sum_{m=1}^{X} E(\varepsilon_{i,k}^K \varepsilon_{j,m}^J) y_m + \sum_{k=1}^{X} x_k \sum_{m=1}^{X} E(\varepsilon_{i,k}^K \varepsilon_{j,m}^K) x_m \end{aligned} \qquad \text{(A.5)}$$

[19] The assumption that we know y with certainty is always valid as policy makers set the amount of government spending. However, it is possible that x cannot be known with complete certainty due to measurement errors or something similar, in which case we would also have to include the variation in x in the calculation of ε^t. Even though it is relatively straight forward to include this source of variance (by means of a linearization of the term $K\,x$ in equation (A.2) around its expected value), we haven't done this here for reasons of simplicity.

The expectation terms in equation (A.5) actually refer to specific elements from the co-variance matrix of the parameter estimates of our linear system. This co-variance matrix is symmetric, and consists of T^2 sub-matrices (associated with each combination of targets) further called $\Omega_{i,j} \quad \forall i, j = 1..Y$ with dimensions (Y+X) × (Y+X). Each sub-matrix in turn is partitioned into 4 sub-matrices of dimensions $Y{\times}Y$, $Y{\times}X$, $X{\times}Y$ and $X{\times}X$, further called $\Omega_{i,j}^{YY}$, $\Omega_{i,j}^{YX}$, $\Omega_{i,j}^{XY}$ and $\Omega_{i,j}^{XX}$, respectively (see also Figure A.1 below). $\Omega_{i,j}^{YY}$ is the co-variance matrix between the expenditure parameter estimates (as captured by the *J* matrix in equation (2)) for the target variables *i* and *j*, while $\Omega_{i,j}^{YX}$ is the co-variance matrix of the expenditure parameter estimates in the equation for target variable *i* and the parameter estimates of the exogenous variables (as captured by the matrix *K*) in the equation for target variable *j*. $\Omega_{i,j}^{XY}$ and $\Omega_{i,j}^{XX}$ are similarly defined. Using this notation, it follows from (A.3) and (A.5) that the variance in *H*, i.e. *V*, can be written as:

$$\begin{aligned} V &= 1/T^2 \sum_{i=1}^{T}\sum_{j=1}^{T}\left(y'\Omega_{i,j}^{YY} y + y'\Omega_{i,j}^{YX} x + x'\Omega_{i,j}^{XY} y + x'\Omega_{i,j}^{XX} x\right) = \\ &= y'\overline{\Omega}^{YY} y + y'\overline{\Omega}^{YX} x + x'\overline{\Omega}^{XY} y + x'\overline{\Omega}^{XX} x \end{aligned} \tag{A.6}$$

where $\overline{\Omega}^{Z}$ represents the arithmetical average over all $\overline{\Omega}_{i,j}^{Z} \ \forall Z = YY, XY, YX, XX$.[20]

Replacing *t* in (1) by (2), and inserting (2) into the objective function, the Lagrangian of the maximization problem (3) is given by:

$$\Phi = \hat{H} - \alpha V + \lambda(B - i' Exp(y)) = i'(\hat{J}\, y + \hat{K}\, x)/T - \alpha V + \lambda(B - i' Exp(y)) \tag{A.7}$$

where λ is the Lagrange multiplier of the budget constraint, and $Exp(y)$ stands for the column-vector $(Exp(y_1)\ Exp(y_2)\ ..\ Exp(y_T))'$. Maximizing (A.7) by a suitable choice of *y* results in the following FOC for *y*:

$$\begin{aligned} \frac{\partial \Phi}{\partial y} &= \frac{\hat{J}' i}{T} - \alpha \frac{\partial V}{\partial y} - \lambda\, Exp(y) = \\ &= \frac{\hat{J}' i}{T} - \alpha\left((\overline{\Omega}^{YY} + \overline{\Omega}^{YY'})\, y + (\overline{\Omega}^{YX} + \overline{\Omega}^{XY'})\, x \right) - \lambda Exp(y) = 0 \end{aligned} \tag{A.8}$$

Note that equations (A.8) and the per capita budget constraint $B = i' Exp(y)$ define *T+1* non-linear simultaneous equations in the *T+1* unknowns *y* and λ, the solution of which we obtain using

[20] Note that the term $1/T^2$ vanishes in the RHS of (A.6) since $\overline{\Omega}^{Z} \equiv \sum_i \sum_j \Omega_{i,j}^{Z} / T^2$.

Mathematica's FindRoot routine. The solution depends on all the elements of the matrix $\hat{J}$, the co-variances in $\overline{\Omega}^{YY}, \overline{\Omega}^{XY}, \overline{\Omega}^{YX}$ and on α. By varying α over a predefined range, we can calculate the corresponding solution of the simultaneous system and so trace the corresponding *EDP*, since the optimum development portfolio must be efficient as well. Note, moreover, that λ is the shadow price of the per capita budget, i.e. it measures by how much the objective function would rise for a one unit increase in the per capita budget.

Figure A.1 Co-variance matrix partitions

		Health *H*		Education *E*		Standard of living *G*	
		Y	*X*	*Y*	*X*	*Y*	*X*
Health *H*	*X*	$\Omega^{YY}_{H,H}$	$\Omega^{YX}_{H,H}$	$\Omega^{YY}_{H,E}$	$\Omega^{YX}_{H,E}$	$\Omega^{YY}_{H,G}$	$\Omega^{YX}_{H,G}$
	Y	$\Omega^{XY}_{H,H}$	$\Omega^{XX}_{H,H}$	$\Omega^{XY}_{H,E}$	$\Omega^{XX}_{H,E}$	$\Omega^{XY}_{H,G}$	$\Omega^{XX}_{H,G}$
Education *E*	*X*	$\Omega^{YY}_{E,H}$	$\Omega^{YX}_{E,H}$	$\Omega^{YY}_{E,E}$	$\Omega^{YX}_{E,E}$	$\Omega^{YY}_{E,G}$	$\Omega^{YX}_{E,G}$
	Y	$\Omega^{XY}_{E,H}$	$\Omega^{XX}_{E,H}$	$\Omega^{XY}_{E,E}$	$\Omega^{XX}_{E,E}$	$\Omega^{XY}_{E,G}$	$\Omega^{XX}_{E,G}$
Standard of living *G*	*X*	$\Omega^{YY}_{G,H}$	$\Omega^{YX}_{G,H}$	$\Omega^{YY}_{G,E}$	$\Omega^{YX}_{G,E}$	$\Omega^{YY}_{G,G}$	$\Omega^{YX}_{G,G}$
	Y	$\Omega^{XY}_{G,H}$	$\Omega^{XX}_{G,H}$	$\Omega^{XY}_{G,E}$	$\Omega^{XX}_{G,E}$	$\Omega^{XY}_{G,G}$	$\Omega^{XX}_{G,G}$

Appendix B. Variance-covariance matrix of parameter estimates

Next to the parameter coefficients of the SUR estimation, their cross-equation variance-covariance matrix plays a crucial role in our model, as shown in Appendix A. The overall structure of this covariance matrix is provided in Figure A.1 above, which shows how the particular $\overline{\Omega}$-partitions taken together make-up the covariance matrix. The numerical values in the covariance matrix are provided in Tables B.1-B.6. Note that in our formal notation, the number of exogenous and endogenous variables included as independent variables in each equation is the same. However, in Table B.1 we have left out those columns and rows from the $\overline{\Omega}$–partitions containing only zero's. These zero-values arise, as the statistically insignificant impact parameters have been set equal to zero, and so are the implied values for the elements in the covariance matrix of such independent variables therefore (if they are not there, they can't co-vary). An example is the independent variable lnhivr (the

HIV-prevalence rate) that contributes to the health target variable but not to the other targets. Consequently the lnhivr rows are missing for the other targets, and so are the corresponding columns, because of the overall symmetry of the covariance matrix.

Table B.1 Covariance matrix elements Ω_{HH}

		lex								
		lngeh	lnurbr	lnpopd	lneser	lntrad	lntbpr	lnhivr	gbcd	_cons
lex	lngeh	128.25								
	lnurbr	-65.09	605.36							
	lnpopd	16.10	66.11	75.47						
	lneser	-118.99	-194.34	-59.38	1056.77					
	lntrad	-101.30	-237.05	1.98	355.64	672.86				
	lntbpr	57.93	79.14	101.14	-65.52	9.43	421.97			
	lnhivr	-30.97	11.09	-10.32	51.84	12.79	-60.88	48.58		
	gbcd	15.79	18.32	-8.28	-114.77	-56.43	-22.67	-43.48	685.98	
	_cons	288.03	-811.29	-918.98	-3846.76	-3092.65	-3038.00	179.44	627.94	50241.67

Table B.2 Covariance matrix elements Ω_{EH}

		lex								
		lngeh	lnurbr	lnpopd	lneser	lntrad	lntbpr	lnhivr	gbcd	_cons
edu	lngeh	18.25	-0.64	1.63	-43.08	-20.24	-3.21	-5.78	8.51	204.37
	lnged	-4.73	-8.33	2.97	54.76	20.50	9.73	3.06	-9.62	-317.25
	lnempr	12.63	-30.70	41.45	-59.43	48.05	18.72	-2.02	-3.81	-175.35
	lneind	-9.99	3.00	-1.82	-33.69	37.09	-2.99	9.23	-7.87	12.62
	lnatss	-2.26	9.35	6.85	-11.77	4.68	-5.85	3.00	-1.34	7.74
	gbcd	-1.48	-2.78	-3.54	11.50	-0.93	2.21	-0.52	87.68	-40.78
	_cons	-55.35	122.87	-205.88	315.66	-346.82	-77.42	-23.63	39.15	1269.57

Table B.3 Covariance matrix elements Ω_{GH}

		lex								
		lngeh	lnurbr	lnpopd	lneser	lntrad	lntbpr	lnhivr	gbcd	_cons
gdp	lngeh	17.99	-8.23	-1.66	-6.47	-29.30	-5.38	-1.22	1.41	153.15
	lngeg	-4.99	-10.06	2.49	8.17	37.34	6.80	1.59	-4.84	-186.36
	lnurbr	-15.13	77.81	5.85	-1.41	-7.06	-1.12	-0.40	5.71	-192.27
	lnpopd	0.52	6.76	7.29	-0.49	-1.68	-0.34	-0.06	0.13	-40.24
	gbcd	-3.20	3.05	0.32	1.38	6.23	1.15	0.26	93.25	-56.11
	_cons	16.91	-204.56	-54.60	-17.17	-79.29	-14.70	-3.14	-14.79	1336.53

Table B.4 Covariance matrix elements Ω_{EE}

		edu						
		lngeh	lnged	lnempr	lneind	lnatss	gbcd	_cons
edu	lngeh	622.87						
	lnged	-393.37	566.21					
	lnempr	731.71	474.89	9773.02				
	lneind	-226.48	138.76	1123.83	1356.13			
	lnatss	-9.36	-161.05	-129.53	-134.61	538.54		
	gbcd	-84.04	95.20	-266.64	28.43	-191.72	1354.19	
	_cons	-2788.06	-2843.36	-48028.6	-8319.12	-117.01	1308.04	246931.1

Table B.5 Covariance matrix elements Ω_{GE}

		edu						
		lngeh	lnged	lnempr	lneind	lnatss	gbcd	_cons
gdp	lngeh	-31.90	17.31	-22.68	25.09	5.87	1.76	32.44
	lngeg	30.23	-22.99	16.56	-29.63	-7.07	-0.91	39.61
	lnurbr	-1.35	5.45	14.86	1.57	-5.25	1.76	-66.84
	lnpopd	-2.29	-0.92	-23.97	5.16	-4.77	2.44	110.01
	gbcd	6.26	-3.62	5.63	-5.49	-1.27	-63.63	3.44
	_cons	-48.25	54.62	21.05	56.45	54.79	-4.09	-514.84

Table B.6 Covariance matrix elements Ω_{GG}

		gdp					
		lngeh	lngeg	lnurbr	lnpopd	gbcd	_cons
gdp	lngeh	187.91					
	lngeg	-190.25	242.19				
	lnurbr	-7.72	-44.01	207.07			
	lnpopd	8.93	-10.17	18.27	20.43		
	gbcd	-38.22	40.48	5.04	-2.00	267.05	
	_cons	421.37	-522.20	-497.07	-109.70	-154.17	3618.29

Appendix C. Country names and labels

Table C.1 Country data availability and labels

		1995	2000	2005			1995	2000	2005
BEN	Benin	x	x	x	MDG	Madagascar	x	x	x
BWA	Botswana	x		x	MWI	Malawi	x	x	
BFA	Burkinoa Faso	x		x	MLI	Mali		x	x
BDI	Burundi	x	x	x	MRT	Mauritania	x	x	x
CMR	Cameroon		x	x	MUS	Mauritius	x	x	x
TCD	Chad			x	NAM	Namibia	x	x	
COM	Comoros		x		NER	Niger	x		x
COG	Congo, Republic of		x	x	RWA	Rwanda			x
CIV	Côte d'Ivoire	x	x		SEN	Senegal	x		x
GNQ	Equatorial Guinea	x	x		ZAF	South Africa	x	x	x
ETH	Ethiopia	x	x	x	SWZ	Swaziland	x		
GMB	Gambia, The	x	x		TGO	Togo	x	x	x
GHA	Ghana	x			UGA	Uganda	x		x
GNB	Giunea-Bisseau		x		ZMB	Zambia	x	x	
LSO	Lesotho		x	x					

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