Social Policy Index: a model-based approach

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Abstract

This paper focuses on the measurement and determinants of the social policy input of a country. We concentrate on what countries do in order to accomplish their social objectives and analyze if they are performing satisfactorily with respect to what they could potentially do. The social policy of a country is considered as a latent variable measured by indicators and influenced by some exogenous causes and hence a MIMIC model is specified and estimated using panel data. We compare our index with other additional measures available in the literature.

Contents

1. Introduction

A Social Policy Index (SPI) is a multidimensional measure (input-based) of each country's social policy that intends to incorporate its priorities in terms of development; in order to allow rankings and comparisons between countries. (Prasad, 2005b and 2006).

The increasing availability of micro as well as macro economic data has been a major contribution to the construction of social indicators since it has allowed to emphasize the multidimensional aspect by providing a wide range of economic, social and political variables.

Several authors have proposed different approaches in order to obtain appropriate measures of development, poverty and inequality and try to explain factors that influence them and evaluate policies that countries adopt to improve their economic and social status.

Two very well known tools often used to compare countries in terms of economic development and social progress are the Gross Domestic Product (GDP) per capita and the Human Development Index (HDI). This last index is composed basically of three indicators which are health, education and income; three dimensions that are considered, by its creators, as the most representative elements of economic and social development.

Most of these indices prioritize the outcome that is the result that a country obtains by applying a particular social policy. UNRISD, pioneer in the involvement of social variables and the creation of social indicators; defines Social Policy as "state intervention that directly affects social welfare, social institutions and social relations. It involves overarching concerns with redistribution, production, reproduction and protection and works in tandem with economic policy in pursuit of national, social and economic goals"[1].

The next section of this dissertation consists in a literature review of articles that used latent variables models for measuring poverty, multidimensional indices or authors that applied this methodology in other areas. Section 3 presents the theoretical framework of some latent

[1] UNRISD 2006. Transformative Social policy: lessons from UNRISD, Research and Policy Brief 5, UNRISD.

variable models. The final theoretical model retained is explained in section 4. Section 5 gives a description of the data and Section 6 presents the empirical model, linking the theory explained in section 4 with the available data. Section 7 discusses the results of the estimations and shows some country rankings. Finally, some concluding remarks are presented in Section 8.

2. Literature Review

Various authors have used latent variables models in fields such as politics, poverty measurement, development measurement and underground economy evaluation. Some articles dealing with empirical applications of these methodologies will be presented. The most common software used to estimate latent variable models is LISREL (Jöreskog and Sörbom 1986). Other software often used are EQS (Bentler 1985) and MPLUS.

Dreher, Kotsogiannis and McCorriston (2005) analyze the causes and consequences of the phenomenon of corruption around the world. They propose a MIMIC model where corruption is designed as the latent variable. The indicators chosen for this model were GDP par capita, private credit (as a share of GDP), and consumption of cement and endeavours as well as capital control restrictions. Other indicators such as the size of shadow economy were also taken into account but unfortunately they were not available for all countries. Explanatory variables chosen for the model included school enrolment rate, rule of law (score for the quality of the legal system) and legal origin (French, German, British). They influenced the latent variable directly. Among their main results, the authors confirmed that economic losses due to corruption are considerably high especially in developing countries; therefore corruption is clearly an obstacle to economic development.

Dreher, Kotsogiannis and McCorriston (2005) analyze the influence of institutions in shadow economy and corruption for 18 OCDE countries by using a Structural Equation Model. These two phenomena are the latent endogenous variables of the model. The results found by these authors showed that the higher the institutional quality, the smaller is the shadow economy. They also found that corruption is negatively affected by the increase of institutional quality.

Krishnakumar (2005) derives multidimensional index of human development by using a Structural Equation Model with the variant of incorporating a set of exogenous variables in the measurement equation (the equation explaining the observed endogenous variables) and another set of exogenous variables in the structural model. The latent endogenous variables are knowledge, health and political freedom, the three most representative dimensions of development. These variables are called capabilities (set of choices). The main result of this paper is that the improvements of political and social environment facilitate the realization of capabilities and raises, very significantly, the level of capabilities themselves. The author concludes by elaborating “capability indices” from latent variables score estimates in order to compare these results with Human Development Index (HDI) and GDP per capita. It is found that countries change significantly their ranking depending on the index chosen.

Breusch (2005) uses MIMIC models in order to estimate the size of the underground economy for numerous countries. The author uses three different applications from other papers. He concludes that the results obtained are very different, not convincing enough and that the use of MIMIC models is not appropriate to fit an underground economy.

Furthermore, it seems interesting to mention that there are some other studies treating latent variable models. We can cite Hansen, Heckman and Mullen (2003); Heldt, Johansson and Vredin (2005); Jöreskog, K.G. and A.S. Goldberger (1975), Nagar and Basu (2001).

Literature offers several approaches for the construction of multidimensional indices. They range from simple or weighted aggregates of different indicators to model-based multidimensional indices incorporating structural relations. In the latter approach, the multidimensional concept that one wants to capture is assumed to be latent, measured through many indicators covering many dimensions. This approach not only yields an aggregate index involving different dimensions but also incorporates the interdependencies and causalities among these dimensions as described by the underlying structural model. This approach which has now become relatively common in well-being measurement (Di Tommaso 2006, Krishnakumar 2007a, 2007b, Krishnakumar and Ballon 2007, Wagle 2005), is also being applied in other areas (Di Tommaso, Raiser and Weeks 2006).

We find this methodology to be particularly relevant in our context as the social policy that a country puts in place is largely determined by the availability of resources (economic, political, and institutional). Thus we can speak of a "feasible" policy given the means and an "actual" policy as reflected by the policy input indicators in various dimensions. This way of looking at both the *causes* and *indicators* of any social policy fits in well with the MIMIC (multiple indicators multiple causes) approach and will help us evaluate if countries are delivering what is "feasible" given their economic and institutional context, in addition to ranking them in terms of actual policy.

Krishnakumar and Ballon (2007) present a framework in order to evaluate countries' social policy effort by using a structural equation model that takes into account the explanations offered by economic theory and the resulting determinants. The authors use the MIMIC model in order to obtain a social policy index that can be used as a basis to compare countries. However, their analysis was only limited to two dimensions of social policy: social spending and social security. Further, the above study only used cross-sectional data whereas we propose to extend the data base to a panel data setting.

3. Latent Variable Models

Latent variables are a representation of concepts that cannot be observed or measured. In order to have an accurate illustration of a specific latent variable, indicators of this latent variable can be selected. Indicators are observable measures that are assumed to be highly correlated (they should even be perfectly correlated in theory) with latent variables. In some cases indexes are constructed by using various indicators in order to have a better representation of the concept. Consequently, an indicator of a latent variable will always include a systematic measurement error, which defines this indicator as a random variable. Indicators are also known to be called measures, manifest variables and proxies. Latent variables can also be designated as unobserved variables, factors or unmeasured variables.

Latent variables can be differentiated by their level of abstractness. Among highly abstract latent variables we have power, social class and intelligence. Education and population size are less abstract latent variables.

The measure, for example, of intelligence cannot be directly observed as it has been implicitly mentioned. This is a particular case because a single observed variable is not taken as an indicator, since it would be very restrictive. Hence, a proposed solution consists in constructing a test composed of questions in numerous areas such as mathematics, geography and history. At the end of this test each person receives a numerical result that can be compared with the results obtained by the other individuals. Nevertheless, even though these kinds of tests do not pretend to completely evaluate such a variable as intelligence, they can give an idea of the intellectual coefficient of an individual.

Another particular case is the phenomenon of suicide. It should normally be categorized as a directly observed variable. But sometimes some suicides are identified as other forms of death due to the sensitive character of the subject. Therefore, since there seems to be a lack of correct information, suicide cannot be directly observed.

Taking into account what has been presented above; we realize that if we are interested in applying econometric estimations to observed variables that are imperfect measures of their corresponding latent variables, customary procedures should not be employed. These procedures give inconsistent estimators because of the presence of measurement errors.

Three different models will be developed in this chapter. For each model the definition of variables, assumptions, covariance matrices and methods of estimation will be explained.

In the first section the general model or Structural Equation Model (SEM) will be analyzed. Jöreskog and Sörbom have importantly contributed to the popularization of this model in the 1970's. Later on, in 1980 other authors such as Bentler and Weeks proposed several modifications to the original model.

Regarding the second section we shall continue to explore the Confirmatory Factor Analysis Model (CFA). It is a specialization of the general model that is much simpler. This model was initially proposed by Spearman in 1904 in an article concerning the measurement of intelligence.

In the third section we shall proceed to explain the Multiple Causes and Multiple Indicators Model (MIMIC). It is also a specialization that is simpler than the Structural Equation Model but more complex than the Factor Analysis Model. The MIMIC models were originally introduced by Jöreskog and Goldberger (1975). This model is the one which will be selected to perform our analysis in this paper.

3.1. Structural Equation Models

This is a model where latent endogenous variables are influenced by other latent endogenous variables and by latent exogenous variables. This interdependent system of equations of unobserved variables, called structural model, is completed by measurement equations, called measurement model, where both latent endogenous variables and latent exogenous variables are observed through a set of indicators. This framework constitutes the "general model".

The *Structural Equations Model* can be presented as:

$$\eta = \mathrm{B}\eta + \Gamma\xi + \zeta$$

$$y = \Lambda_y \eta + \varepsilon$$

$$x = \Lambda_x \xi + \delta \quad ,$$

under the following assumptions:

$E(\eta) = 0$, $E(\xi) = 0$, $E(\varepsilon) = 0$, $E(\delta) = 0$, $E(\zeta) = 0$,

and also

$E(\varepsilon\eta') = 0$, $E(\varepsilon\xi') = 0$, $E(\varepsilon\delta') = 0$, $E(\delta\xi') = 0$, $E(\delta\eta') = 0$,
$E(\delta\varepsilon') = 0$, $E(\zeta\xi') = 0$;

$V(\xi) = \Phi$, $V(\zeta) = \Psi$, $V(\varepsilon) = \Theta$, $V(\delta) = \Omega$;

where:

η denotes the vector containing latent endogenous variables $(m \times 1)$.

ξ denotes the vector containing latent exogenous variables $(n \times 1)$.

B denotes the coefficient matrix for latent endogenous variables $(m \times m)$.

Γ denotes the coefficient matrix for latent exogenous variables $(m \times n)$.

ζ denotes the vector containing latent errors. $(m \times 1)$.

y denotes the vector containing observed indicators of η $(p \times 1)$.

x denotes the vector containing observed indicators of ξ $(q \times 1)$.

ε denotes the vector containing the measurement errors for y $(p \times 1)$.

δ denotes the vector containing the measurement errors for x $(q \times 1)$.

Λ_y denotes the coefficient matrix relating y to η $(p \times m)$.

Λ_x denotes the coefficient matrix relating x to ξ $(q \times n)$.

Φ denotes the covariance matrix of ξ $(n \times n)$.

Ψ denotes the covariance matrix of ζ ($m \times m$).

Θ denotes the covariance matrix of ε ($p \times p$).

Ω denotes the covariance matrix of δ ($q \times q$).

We have therefore assumed that the observations are centered, all error terms have an expected value equal to zero, measurement errors are uncorrelated between them and with latent variables whether they are endogenous or exogenous. The hypothesis of an inexistence of correlation between latent exogenous variables and latent errors has also been done above. Latent errors are assumed homoscedastic and non-autocorrelated, thus the corresponding covariance matrix is diagonal.

It can be noticed that B is a particular matrix. Its diagonal is always equal to zero. This means that a latent endogenous variable does not have an effect on itself. If another element of the matrix is equal to zero, it indicates that a specific latent endogenous variable has no effect on the latent endogenous variable that is being explained.

The model can also be written:

$$\eta = \mathrm{B}\eta + \Gamma\xi + \zeta\,,$$
$$\mathrm{B}\eta - \eta + \Gamma\xi + \zeta = 0\,,$$
$$(\mathrm{B} - \mathrm{I})\eta + \Gamma\xi + \zeta = 0\,,$$
$$\mathrm{A}\eta + \Gamma\xi + \zeta = 0\,,$$

where $\mathrm{A} = (\mathrm{B} - \mathrm{I})$.

The latent endogenous variables can be isolated in the equation in order to be explained by the latent exogenous variables. This implies that the matrix $(\mathrm{I} - \mathrm{B})$ is non singular, hence the matrix $(\mathrm{I} - \mathrm{B})^{-1}$ exists. This form is called the reduced form and it will be useful to derive the covariance matrices of the indicators.

$$\mathrm{A}\eta + \Gamma\xi + \zeta = 0\,,$$
$$-\mathrm{A}\eta = \Gamma\xi + \zeta\,,$$

$$\eta = -\mathrm{A}^{-1}\Gamma\xi - \mathrm{A}^{-1}\zeta \,,$$

$$\eta = (\mathrm{I}-\mathrm{B})^{-1}\Gamma\xi + (\mathrm{I}-\mathrm{B})^{-1}\zeta \,.$$

The theoretical expressions of the covariance matrix for y and for x in function of the unknown parameters θ are given by:

$$\begin{aligned}\Sigma_y(\theta) &= E(yy') \\ &= \Lambda_y E(\eta\eta')\Lambda_y' + \Theta \,, \\ &= \Lambda_y (\mathrm{I}-\mathrm{B})^{-1}(\Gamma\Phi\Gamma' + \Psi)[(\mathrm{I}-\mathrm{B})^{-1}]'\Lambda_y' + \Theta\end{aligned}$$

$$\begin{aligned}\Sigma_x(\theta) &= E(xx') \\ &= \Lambda_x \Phi \Lambda_x' + \Omega\end{aligned}$$

The covariance matrix of y with x can be written as follows:

$$\begin{aligned}\Sigma_{xy}(\theta) &= E(yx') \\ &= \Lambda_y E(\eta\xi')\Lambda_x' \\ &= \Lambda_y (\mathrm{I}-\mathrm{B})^{-1}\Gamma\Phi\Lambda_x'\end{aligned}$$

By taking each one of these covariance matrices and putting them in a single covariance matrix for y and x we find:

$$\Sigma(\theta) = \begin{bmatrix} \Lambda_y (\mathrm{I}-\mathrm{B})^{-1}(\Gamma\Phi\Gamma' + \Psi)[(\mathrm{I}-\mathrm{B})^{-1}]'\Lambda_y' + \Theta & \Lambda_y (\mathrm{I}-\mathrm{B})^{-1}\Gamma\Phi\Lambda_x' \\ \Lambda_x \Phi \Gamma' [(\mathrm{I}-\mathrm{B})^{-1}]'\Lambda_y' & \Lambda_x \Phi \Lambda_x' + \Omega \end{bmatrix}$$

All unknown parameters are included in the vector called θ.

Before proceeding to estimate the parameters, it is necessary to verify that the identification conditions for this model are filled. In general we can say that the model is identified if there are no two vectors of parameters giving the same covariance matrix. In other words the values of θ must be unique. It is important to take into account any *a priori* constraint already established for the parameters. The constrained parameters will not be included in the vector of unknown parameters.

The general idea in order to estimate the parameters is to minimize the distance in a specific metric between the empirical variance covariance matrix called "M" (calculated by using the observed variables) and the theoretical covariance matrix shown above. Three methods of estimation can be implemented: Maximum Likelihood (ML), Generalized Least Squares (GLS) and Unweighted Least Squares (ULS). The functions to minimize are:

$$
\begin{cases}
\underset{\theta}{T_{ML}} = \log|\Sigma(\theta)| + tr\{M\Sigma^{-1}(\theta)\} - \log|M| - (p+q) \\
\underset{\theta}{T_{GLS}} = \left(\frac{1}{2}\right) tr\{[\mathrm{I} - \Sigma(\theta)M^{-1}]^2\} \\
\underset{\theta}{T_{ULS}} = \left(\frac{1}{2}\right) tr\{[M - \Sigma(\theta)]^2\}
\end{cases}
$$

As it can be noticed all functions are minimized with respect to the unknown parameters vector θ.

Once we have found the parameter estimates they can be used to estimate the values of latent variables.

3.2. Confirmatory Factor Analysis

The *Confirmatory Factor Analysis* is a special case of the "general model" (Structural Equation Models) presented above. In this model a set of indicators or observed variables are influenced by one or more latent variables. The coefficient matrix accompanying the latent variables represent the effects of these latter ones on the indicators, and the error terms in the equation are the systematic measurement errors which are supposed to be uncorrelated with the unobservable variables (factors). The model can be exposed as:

$$y = \Lambda_y \eta + \varepsilon,$$

where

η denotes the vector containing latent variables or factors ($m \times 1$).

y denotes the vector containing observed indicators of η ($p \times 1$).

Λ_y denotes the coefficient matrix relating y to η ($p \times m$).

ε denotes the vector containing the measurement errors for y ($p \times 1$).

Θ denotes the covariance matrix of ε ($p \times p$).

H denotes the covariance matrix of η ($m \times m$).

The error term is usually divided in two parts:

$$\varepsilon = \sigma + \nu$$

where σ is the specific variance of each variable and ν is the random element. This specification does not alter our hypothesis because both parts form the total measurement error that is considered as random.

The covariance matrix of y can be written as:

$$\begin{aligned}\Sigma_y(\theta) &= E(yy') \\ &= \Lambda_y E(\eta\eta')\Lambda_y' + \Theta \\ &= \Lambda_y \mathrm{H} \Lambda_y' + \Theta,\end{aligned}$$

Latent variables are supposed, in this case, to be random. The underlying assumptions of the general model about the measurement errors are still applicable. As we have already mentioned, factors and indicators are deviations from their respected means without loss of generality.

Concerning the identification of the Factor Analysis Model, some restrictions on the parameters must be done since the model is underidentified. What most commonly is assumed is that errors of measurement are non-autocorrelated, hence their corresponding covariance matrix is diagonal. If identification problems persist, other assumptions must be added, for example, a usual solution proposed is to pose the covariance matrix of the latent variables as the identity matrix.

The estimation of the parameters can be done by the same methods mentioned for the Structural Equations Models. The idea of the minimization is the same: we must find values of the parameters as close as possible to those of the empirical covariance matrix. The functions to minimize with respect to θ (vector containing all unknown parameters) are:

$$\begin{cases} \underset{\theta}{T_{ML}} = \log|\Sigma_y(\theta)| + tr\{M_y \Sigma_y^{-1}(\theta)\} - \log|M_y| - p \\ \underset{\theta}{T_{GLS}} = \left(\frac{1}{2}\right) tr\{[\mathrm{I} - \Sigma_y(\theta) M_y^{-1}]^2\} \\ \underset{\theta}{T_{ULS}} = \left(\frac{1}{2}\right) tr\{[M_y - \Sigma_y(\theta)]^2\} \end{cases}$$

Once the parameters are obtained, the values of latent variables can also be estimated by applying, for example, the method of factor score estimation:

$$\hat{\eta} = \hat{\mathrm{H}} \hat{\Lambda}'_y \hat{\Sigma}_y^{-1} y$$

where $\hat{\mathrm{H}}$, $\hat{\Lambda}_y$ and $\hat{\Sigma}_y$ are estimates of H, Λ_y and Σ_y respectively.

There is also another major approach of factor analysis called *Explanatory Factor Analysis.* Among the main differences existing between the Confirmatory and the Explanatory analysis we can find that in the first approach the observed variables do not have to be influenced by each factor, the quantity of unobserved variables are determined before the analysis and the measurement errors can be correlated over time.

3.3 MIMIC Models

The *Multiple Indicators and Multiple Causes* Models are another particular case of the Structural Equation Models. In the context of this model a single latent variable not only manifests itself through some observed variables but it is caused by other exogenous variables that can be measured with exactitude. The measurement equation contains, as always, measurement errors and the causal relationship (the equation implying exogenous variables that affect the factor) contains disturbance terms as well. The model can be written as:

$$\eta = \Gamma' x + \zeta$$
$$y = \Lambda_y \eta + \varepsilon$$
$$x = \xi$$

η denotes a scalar representing a latent variable or factor. (1×1).

y denotes the vector containing observed indicators of η $(p\times1)$.

Λ_y denotes the coefficient vector relating y to η $(p\times1)$.

ε denotes the vector containing the measurement errors for y $(p\times1)$.

Γ denotes the coefficient vector for latent exogenous variables $(n\times1)$.

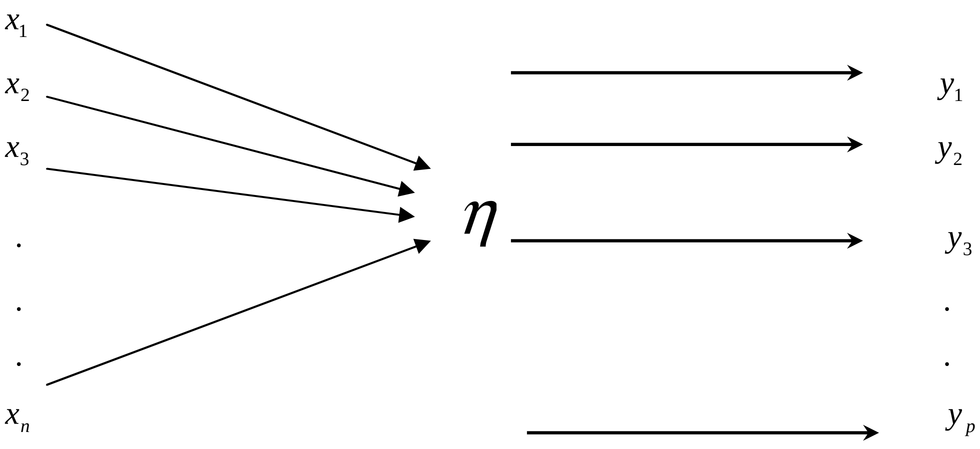
ζ denotes the scalar representing the error term in causal relationship (1×1).

x denotes the vector containing exogenous variables $(n\times1)$.

Θ denotes the covariance matrix of ε $(p\times p)$.

ϕ denotes the variance of ζ (1×1).

The following diagram represents the relations between variables:



It is assumed that the error terms ε and ζ have zero means and are non correlated with each other. In some cases the hypothesis of Θ as a diagonal matrix is done as well. In other words we suppose that measurement errors are non-autocorrelated.

A sufficient but not necessary condition for identification of this model is that the number of indicators is equal or greater than two and the number of exogenous variables is equal or greater than one. This means that:

$$p \geq 2 \qquad \text{and} \qquad n \geq 1$$

The expression of the covariance matrix of y is given by:

$$\begin{aligned}
\Sigma_y(\theta) &= E(yy') \\
&= E[(\Lambda_y \eta + \varepsilon)(\eta' \Lambda_y^{'} + \varepsilon')] \\
&= \Lambda_y E(\eta\eta')\Lambda_y^{'} + E(\varepsilon\varepsilon') \\
&= \phi \Lambda_y \Lambda_y^{'} + \Theta
\end{aligned}$$

Sometimes by convention the variance of the factor is usually assumed as the unity ($\phi = 1$).

So:

$$\Sigma_y(\theta) = \Lambda_y \Lambda_y^{'} + \Theta$$

To estimate the parameters the same procedures already exposed in the other sections can be used. For this model the Maximum Likelihood method (ML) is typically employed.

For all the models that have until now been explained, alternative estimators have been proposed when numerical, statistical or econometric problems appear. If by applying ML, GLS and ULS the number or iterations are considerable so that the computationally cost is very high, Instrumental Variables estimator (IV/GMM) is an appropriate option for this inconvenience. In cases where the normality hypothesis is restrictive the use of Weighted Least Squares is highly recommended. Both underlying alternatives give consistent estimators.

4. Theoretical Model

The theoretical model for this framework is a mixed MIMIC model for two-level data. The model will contain a random intercept in order to capture the specific characteristics of each country. Since there are no time effects, we can consider we are in a multi-level model where individuals (countries in our case) are clusters. This is to separate changes within one individual and differences between individuals.

Therefore, the whole model can be separated in two parts. The within part (variation across individuals and over time) can be written as follows:

$$\left\{\begin{array}{lll}
(1) & y_{jit} = \alpha_j + \underset{\substack{\uparrow \\ \text{between} \\ \text{latent} \\ \text{variable}}}{\mu_{ji}} + \lambda_j \underset{\substack{\uparrow \\ \text{within} \\ \text{latent} \\ \text{variable}}}{f_{wit}} + \delta_j' w_{it} + u_{jit} & \begin{array}{l} j = 1 \ldots J \\ i = 1 \ldots N \\ t = 1 \ldots T \end{array} \\
(2) & f_{wit} = \beta' x_{it} + v_{it} &
\end{array}\right.$$

where (1) represents the measurement equation and (2) represents the causal relationship, J is the number of indicators , N is the number of individuals, T is the number of years, and:

y_{jit} denotes a scalar representing indicator j for individual i at time t,

α_j denotes the specific intercept of indicator j,

μ_{ji} denotes a random intercept of indicator j and individual i,

λ_j denotes the factor loading relating the latent variable f_{wit} to indicator j,

f_{wit} denotes the within latent variable for individual i at time t,

δ_j denotes a vector containing coefficients relating observed exogenous variables to indicator j.

w_{it} denotes a vector of observed exogenous variables for indicator j,

u_{it} denotes the error term in equation (1).

x_{it} denotes a vector of observed exogenous variables for the within latent variable,

β denotes a vector of coefficients relating x_{it} to f_{wit},

v_{it} denotes the error term in (2).

The between part of the model (variation only between clusters) can be written as follows:

$$\begin{cases} (3) \quad \mu_{ji} = \rho_j f_{bi} + \varepsilon_{ji} & j = 1...J \\ & i = 1...N \\ (4) \quad f_{bi} = \theta' m_i + e_i & \end{cases}$$

where (3) represents the measurement equation and (4) the causal relationship of this level, and:

ρ_j denotes the factor loading relating f_{bi} to random intercept μ_{ji},

f_{bi} denotes the between latent variable for each individual i,

ε_{ji} denotes the error term in equation (3),

θ denotes a vector of coefficients relating m_i to f_{bi},

m_i denotes a vector containing observed exogenous variables in equation (4) that vary only between clusters (time invariant),

e_i denotes the error term in equation (4).

5. Data and Exploratory Analysis

This empirical application needed different types of variables such as economic, social, political and demographic variables. Because of this fact, the data was collected from different sources: World Development Indicators (WDI), Governance Matters, International Social Security Association (ISSA), Country Indicators for Foreign Policy (CIFP), International Country Risk Guide (ICRG), Human Development Reports (HDR), International Labour Organization (ILO), World Institute for Development Economic Research (UNU-WIDER) and KOF Index of Globalization.

The main objective was to find data for as many countries and years as possible in view of the fact that one of the interests of this paper is working with cross sectional and time series data and that one can expect to have an important number of missing values in this case. And it was confirmed when the first database was constructed. First of all, some countries had almost no data at all and they were consequently removed. Second, even if there were data from 1998 to 2006, after some exploratory analysis it was decided to drop years 1998, 2005 and 2006 because some variables were completely missing for these periods. Third, countries that had no social security variables at all were also removed, since these variables were available either for a country in all periods or not available in any period.

The finally data set consists in 6 years (1999-2004) for 98 countries. Removing all countries with missing data would not have left enough countries to perform our analysis. This could probably create numerical convergence problems for our parameters estimations. Starting by the fact that there is not a single year with complete data for all variables. However, dropping variables was not a solution either because it implies taking away possible explanation for the model without even testing it. Therefore, it was inevitable to contain missing values in the final database in spite of efforts made to reduce this inconvenience as much as possible.

This data allows us to consider two policy dimensions: social expenditure and social security. There are more policy dimensions that would have been interesting to study but finding panel data for those other dimensions was a major problem.

The latent variables or capabilities are the potential social spending and the potential social security policies. For the first one there are two indicators: public health expenditure as a percentage of GDP and public education expenditure as a percentage of GDP. For the second one there are three indicators being the government's coverage and redistribution of social security program for three categories: old age, disability and survivors, sickness and maternity and work injury. These variables were found in text form and were recoded by using the U.S Social Security Administration Methodology. This system uses a scale from 0 to 9, where 9 represents the maximal coverage and 0 corresponds to an absence of coverage. Table 1 shows the scores of this variable in detail.

Table 1

Score	Type of coverage and redistribution of the social security program
9	Universal
8	Compulsory social insurance with state subsidy
7.5	Compulsory social insurance with no state subsidy
7	Compulsory insurance with state subsidy, but one or more groups excluded
6.5	Compulsory insurance with no state subsidy, with one or more groups excluded
6	Contributory social insurance, but risk based differentiation with state subsidy
5.5	Contributory social insurance, but risk based differentiation with no state subsidy
5	Private (mandatory) with no state subsidy
4	Provident fund
3	Employer liability
2	Social assitance (means tested)
1	Voluntary private insurance
0	No social policy

Exogenous variables that influence capabilities and exogenous variables that influence the indicators were selected from Ballon and Krishnakumar (2006), Baquir (2002), Prasad (2006). These are variables that based on economic theory, determine the government's size and composition.

Three sorts of variables were used as exogenous variables. Economic and demographic determinants were used in the structural model; political determinants were included in the measurement model. Table 2 gives a description of all our variables.

Table 2

F* Potential social policy		**y Actual Policy - observed input indicators**	
F1*	Potential social spending	HEALTH	Public Health Expenditure % GDP
		EDUC	Public Education Expenditure % GDP
		ODS	Old age, disability and survivors
F2*	Potential social security	SM	Sickness and maternity
		WI	Work injury

x Oberved exogenous of endogenous (in the structural model)		**w Observed exogenous of indicators (in the measurement model)**	
Economic determinants		***Political Determinants***	
GDP	Per capita GDP	VA	Voice and Accountability
GROWTH	Growth rate	PS	Political Stability
DEF	Fiscal deficit as a % GDP	GV	Government Effectiveness
KOF	KOF index of Globalization	COR	Control of Corruption
GINI	GINI Inequality Measure		
Demographic determinants			
URBAN	% of urban population (urban)		
POP014	% population 14 years old or younger		
POP65	% population 65 years old or older		
LIFE	Life expectancy (in years)		

All the exogenous variables are continuous variables. Political determinants are measured in units from about -2.5 to 2.5, where the higher the value of the political score the better the outcome of governance. It is relevant to explain the difference between the variables "Voice and Accountability" that can be considered as a Democracy index by the fact that it measures the participation to elect the government and the freedom of expression and press; whereas "Political Stability" represents how citizens believe that their government can be affected by internal or external conflicts such as terrorism.

The KOF index of Globalization takes into account economic, social and political dimensions. These dimensions are measured by using actual economic flows, economic restrictions, data on information flows, data on personal contact and data on cultural proximity.

Two interesting facts were found when carrying out an exploratory analysis of the data. The first one is the very small variation for social security variables within clusters. Table 3 shows that the between variance represents at least 90% of the overall variance for these variables. Besides, since the coverage is not a continuous variable, it is almost certain that the within variance does not come from small changes over the years but from one or two medium changes during the whole period. This suggests that this variable is almost invariant within clusters, which could bring some problems when estimating the within model.

Table 3

Variable		**Mean**	**Std. Dev.**	**Min**	**Max**
ODS	overall	6.909014	1.379691	2	9
	between		1.354222	2	9
	within		0.2919758	5.659014	9.07568
SM	overall	6.105442	2.235101	0	9
	between		2.217341	0	9
	within		0.3477844	1.522109	9.438776
WI	overall	6.691327	1.509045	3	9
	between		1.402737	3	8
	within		0.5712321	3.691327	10.02466

The second fact to take into account is the very high level of correlation between political determinants. Table 4 reports the matrix correlations between the political variables. One can expect that one or two of these determinants are able to capture the effect of the others. Thus, putting all these variables together in the model may give significance only for one or two of them.

Table 4

	VA	PS	GOV	COR
VA	1.0000			
PS	0.8656	1.0000		
GOV	0.8754	0.8469	1.0000	
COR	0.8447	0.8255	0.9706	1.0000

6. Empirical Model

The potential or feasible level of social policy that a country can supply is determined by its economic, social and demographic contexts. But in reality this level is not attained because of political and institutional frameworks and other specific characteristics of each country.
As a result of this situation, we have a difference between the "potential" social policy, and the "actual" policy performed by the country.

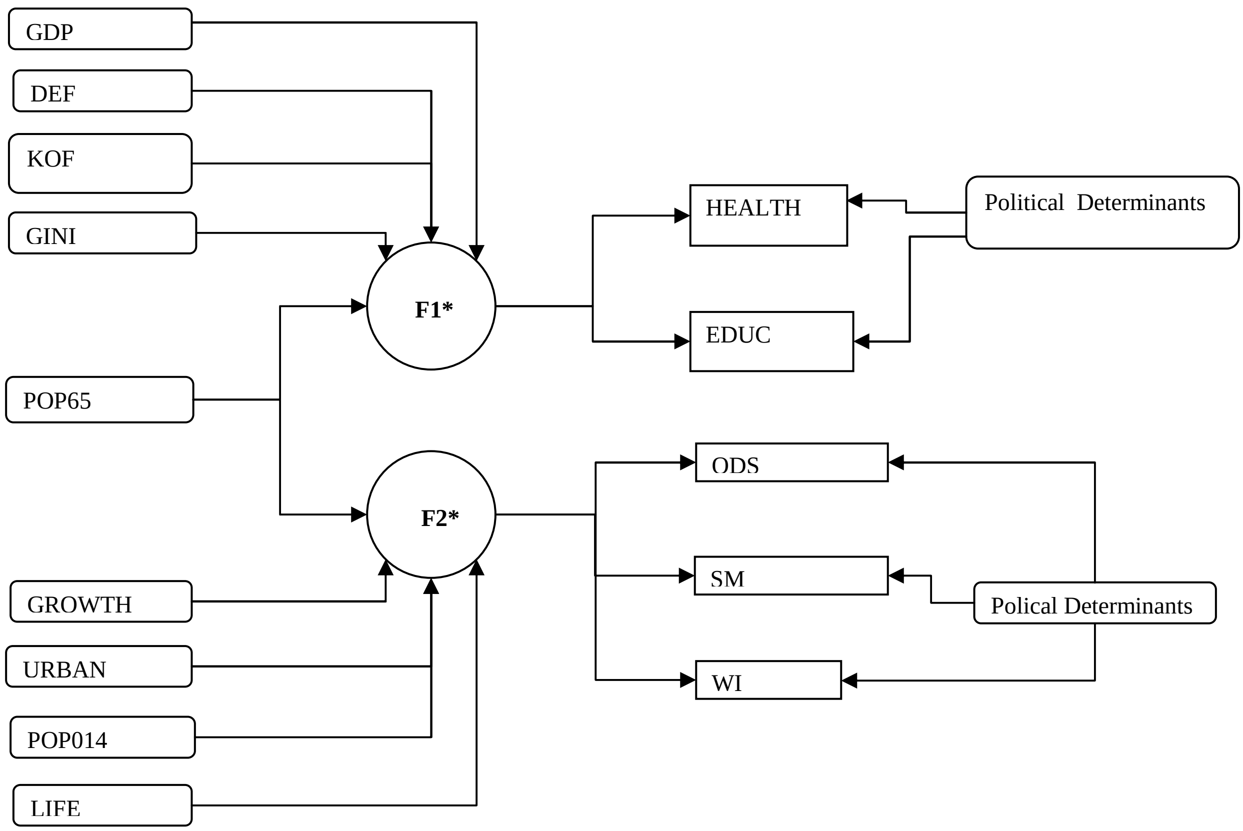
The potential social policy is our latent variable (or factor), this level being unobservable, and it is represented by causal relationships in the theoretical model. The difference between the two policy levels is given by measurement equations in the theoretical model.

The relations of this model can be described as follows:

The potential social expenditure determines health expenditure and education expenditure and is caused by GDP per capita, fiscal deficit, KOF Index of Globalization and Gini Index. Public health expenditure and education expenditure are influenced at the same time by political variables.

The potential social security determines the coverage of the three categories mentioned above and is caused by the four demographic variables plus the growth rate. The coverage and distribution of social security programs are influenced at the same time by political variables.

The following diagram describes the structure of this MIMIC model.



7. Results and Country Rankings

The results of this empirical application are shown in Tables 3 to 8. The estimations were made in MPLUS by using maximum likelihood method and missing values were imputed by using EM algorithm. However, missing values were not allowed for covariates, then we were forced to lose information for some countries.

In Table 5 we have estimations for our measurement model - within level. The factor loadings for the potential social spending are positive and significant. Then, a unit change of potential social spending increases public health and education expenditure as a % of GDP of 0.87 and 0.832 units respectively.

In the social security dimension we have the right signs, all positive for the three indicators but they are non significant. This is a result we have anticipated to some extent due to the small proportion of the within variance on the total variance for social security indicators. Almost all the variance is concentrated between clusters rather than within clusters. Therefore, the within factor for this dimension turns out to be insignificant.

Table 5

Measurement Equation Factor Loadings - Within Level

Potential Social Policy		Parameter		Standardized Coefficient	R squared
Spending					
EDUC	Public Education Expenditure % GDP	1.000	-	0.832	0.692
HEALTH	Public Health Expenditure % GDP	2.489	***	0.870	0.981
Security					
ODS	Old age, Disability and Survivors	1.000	-	0.030	0.001
SM	Sickness and Maternity	37.227	-	1.000	0.999
WI	Work Injury	33.847	-	0.624	0.390

*** denotes significance at 1% level

Table 6 shows the estimates of causal relationships at the within level. GDP per capita, Gini index and population aged 65 and above have a positive and significant impact on potential social spending. An interesting fact is that GDP per capita and population aged 65 and above have almost the same influence (0.631 and 0.632 respectively) on potential social spending. We could have expected GDP per capita to have by far the most important effect knowing that economic resources are fundamental to put into practice social policies. But this result shows that this factor is as important as the proportion of this part (65 or more) of the population. One possible explanation to this interesting outcome is that when a population gets proportionally older the government loses a source of revenue to finance the retirement of these people and it is consequently forced to spend more money on them.

The positive and significant effect of Gini inequality measure illustrates that unequal societies will cost more in terms of social policy. Fiscal deficit has a negative and significant impact on the capacity for social spending. Some financial resources that could be used to enhance the social policy are finally utilized to decrease the fiscal deficit and that is why this variable reduces this capability for any country. KOF Index of Globalization turns out to be insignificant in this part of the model.

There are no causal relationships estimates for the social security dimensions for the same reasons evoked above. The within variation for this part is almost negligible. Hence, we can practically drop the within part of the model for this dimension since estimations always gave non significant results, which in some way corroborate our findings in the exploratory analysis.

Table 6

Causal relationships - Within Level

Economic and Demographic variables		**Parameter**		**Standardized Coefficient**	**R squared**
Potential Social Spending					0.962
GDP	Per capita GDP	0.031	***	0.631	
DEF	Fiscal Deficit	-0.027	***	-0.179	
GINI	Gini index	0.007	**	0.110	
POP65	Pop 65 or more	0.0072	***	0.632	

,* denotes significance at 5% and 1% levels respectively

Among the political variables, Voice and Accountability turns out to be significant and have a positive influence on public health expenditure (see Table 7). Therefore, this factor affects the transformation of "potential" spending into "actual" spending. The higher a government's levels of democracy, participation and freedom of expression and the greater the part of its revenue that it will be provided to social spending (public health in this case). The other political variables showed no significant effects.

Table 7

Social Spending Measurement Equation Coefficients – Within level

Political Determinants		Public Health Expenditure % GDP: Parameter		Standardized Coefficient
VA	Voice and Accountability	0.145	**	0.149

** denotes significance at 5% level

Table 8 presents measurement equations estimates for the between part of the model. This time all factor loadings for both policy dimensions are very significant and have positive signs. It verifies that the social security dimension has no problem on the between level since there is an important variation between countries.

Table 8

Measurement Equation Factor Loadings - Between Level

Potential Social Policy		Parameter		Standardized Coefficient	R squared
Spending	**(intercepts)**				
EDUC	Public Education Expenditure % GDP	1.000	-	0.809	0.655
HEALTH	Public Health Expenditure % GDP	0.732	**	0.710	0.504
Security	**(means)**				
ODS	Old age, Disability and Survivors	1.000	-	0.594	0.489
SM	Sickness and Maternity	1.599	***	0.758	0.574
WI	Work Injury	1.387	***	0.807	0.651

*** denotes significance at 1% level

Table 9 reports the estimation results for causal relationships in the between model. In our database there were no exogenous variables varying only between clusters. All available variables changed over time. But given the fact that we could not include causal relationships for the social security dimension in the within part, we calculated means of exogenous variables that were supposed to be used in the within level in order to use them in the between level. These variables are: growth rate, % of population 14 years old or younger, % of population 65 years old or older and % urban population. The regression of potential social security on each one of these variables provided significant coefficients except for growth rate. Nevertheless, when all variables were together in the regression, there was only one who remained significant and all the other ones did not bring any more explanation to the model. We decided to use principal components method (Hotelling 1933, Ram 1982, Slottje 1991) by using the significant variables and we kept the first principal component denoted as P1. This component has a positive impact on potential social security and it is significant. As a result, urban societies having important proportions of depending populations (14 years old or younger and 65 years old or older) and where people lives more are the most demanding of social security coverage.

Table 9

Causal relationships - Between level

Demographic variables		**Parameter**		**Standardized Coefficient**	**R squared**
Potential Social Security					0.333
P1	First principal component	0.325	***	0.577	

*** denotes significance at 1% level

In table 10 it is shown that political stability has a positive and significant effect on social security coverage (old age, disability and survivors coverage). This confirms that it is not only important to have a democratic government but also to have stability and absence of violence inside the country. Usually, countries having internal conflicts or high levels of domestic violence, spend a part of its budget to resolve these problems. This expenditure could be differently attributed if they did not have this kind of inconvenient. Consequently, states politically stable have an additional source to finance social security coverage (which implies better scores of socials security) comparing to those who are not. The other political variables showed no significant effects.

Table 10

Social Security Measurement Equation Coefficients – Between level

		Old age, disability and survivors		
Political Determinants		**Parameter**		**Standardized Coefficient**
PS	Political Stability	0.155	**	0.192

** denotes significance at 5% level

Finally, fit indices show a reasonable / good fit of the model. The Tucker and Levis incremental fit index (TLI) is considered reasonable (acceptable) if the values are between 0.90 and 0.95 and good if they are above 0.95. In our case, this index value is 0.94. Besides, The Root Mean Squared Error of Approximation (RMSEA) is 0.036. Good models should have values of 0.05 or less.

One of the most important objectives concerning the creation of a social policy index (SPI) is that it will allow not only to compare how countries perform in terms social policy but it shall help us evaluate if the are performing better or worse than they should with their respective available resources. The construction of Social Policy Index will permit to compare countries in terms of social policy thanks to the establishment of a ranking.

Once the SPI is obtained, the most important aim for this index is to have an impact in a government's decisions. In other words, the main goal is to give an image of countries' social policy results in order to help to improve future social policy implementation.

Due to the missing values on the covariates of our database, we do not have latent factors for the 98 countries that were included in the analysis either for the six years. The number of countries having scores for each year is unbalanced. The "potential social spending" factor is available for the period 2000-2004 for 29 countries. Table shows the ranking of these 29 countries in term of "potential social spending" from 2000 to 2004. If the country has a (+) sign, it means that it has improved its position compared with the past year. If it is a (-) sign, it means that the country got a worse position compared with the past year. Finally if nothing is written next to the country, it means that its position did not change from one year to the other.

Table 11

RANK_00	RANK_01	RANK_02	RANK_03	RANK_04
Luxembourg	Luxembourg	Luxembourg	Luxembourg	Luxembourg
Denmark	Sweden (+)	Norway (+)	Austria (+)	Austria
Sweden	Norway (+)	Sweden (-)	Norway (-)	France (+)
Germany	Germany	Denmark (+)	United Kingdom (+)	Norway (-)
Belgium	Denmark (-)	United Kingdom (+)	Sweden (-)	United Kingdom (-)
United Kingdom	United Kingdom	Germany (-)	Denmark (-)	Sweden (-)
France	Belgium (-)	France (+)	Germany (-)	Belgium (+)
Norway	France (-)	Belgium (-)	France (-)	Denmark (-)
Austria	Netherlands (+)	Netherlands	Netherlands	Germany (-)
Netherlands	Finland (+)	Finland	Belgium (-)	Finland (+)
Spain	Austria (-)	Australia (+)	Finland (-)	Netherlands (-)
Australia	Spain (-)	Spain	Spain	Portugal (+)
Finland	Australia (-)	Austria (-)	Portugal (+)	Spain (-)
Portugal	Portugal	Portugal	Australia (-)	Australia
Uruguay	Uruguay	Uruguay	Hungary (+)	Slovenia (+)
Slovenia	Slovenia	Slovenia	Slovenia	Latvia (+)
Estonia	Czech Republic (+)	Hungary (+)	Czech Republic (+)	Hungary (-)
Latvia	Hungary (+)	Czech Republic (-)	Bulgaria (+)	Uruguay (+)
Czech Republic	Poland (+)	Bulgaria(+)	Lithuania (+)	Lithuania
Hungary	Latvia (-)	Poland (-)	Ukraine (+)	Czech Republic (-)
Lithuania	Estonia (-)	Latvia (-)	Poland (-)	Ukraine (-)
Bulgaria	Lithuania (-)	Estonia (-)	Latvia (-)	Bulgaria (-)
Poland	Bulgaria (-)	Ukraine (+)	Estonia (-)	Poland (-)
Ukraine	Ukraine	Lithuania (-)	Uruguay (-)	Estonia (-)
Venezuela, RB	Costa Rica (+)	Costa Rica	Costa Rica	Sri Lanka (+)
Sri Lanka	Sri Lanka	Sri Lanka	Sri Lanka	Costa Rica (-)
Costa Rica	Peru (+)	Venezuela, RB (+)	Venezuela, RB	Venezuela, RB
Peru	Venezuela, RB (-)	Peru (-)	Peru	Guatemala (+)
Guatemala	Guatemala	Guatemala	Guatemala	Peru (-)

There is no a "potential social security" factor varying over the years as this factor was not significant in the estimations. A between factor is available which is invariant over time.

The year with the greatest number of factors is 2003. There are estimates for 68 countries. Table 12 reports for the 68 countries in 2003 their ranking of: potential social spending (MIMIC1), potential social spending plus potential social security (MIMIC2) and Human Development Index (HDI). The last two columns of this table show the difference of HDI and MIMIC1 and MIMIC2. If this difference is positive, then the country is not using all its potential and its performance is worse than one could have expected. If this difference is negative, it illustrates that the country's social policy is giving better results than expected given its social, economic demographic and political situation.

Table 12

COUNTRY	MIMIC1	MIMIC2	HDI	DIFFERENCE HDI-MIMIC1	DIFFERENCE HDI-MIMIC2
Norway	3	2	1	-2	-1
Australia	19	39	2	-17	-37
Luxembourg	1	1	3	2	2
Canada	15	19	4	-11	-15
Sweden	6	7	5	-1	-2
Ireland	14	21	6	-8	-15
Belgium	12	8	7	-5	-1
United States	4	16	8	4	-8
Netherlands	11	11	9	-2	-2
Finland	13	18	10	-3	-8
Denmark	7	29	11	4	-18
United Kingdom	5	3	12	7	9
France	10	4	13	3	9
Austria	2	6	14	12	8
Italy	8	5	15	7	10
New Zealand	28	10	16	-12	6
Germany	9	9	17	8	8
Spain	17	12	18	1	6
Israel	20	22	19	-1	-3
Greece	16	13	20	4	7
Singapore	27	61	21	-6	-40
Slovenia	22	14	22	0	8
Portugal	18	28	23	5	-5
Korea, Rep.	37	36	24	-13	-12
Cyprus	23	15	25	2	10
Czech Republic	25	30	26	1	-4

COUNTRY	MIMIC1	MIMIC2	HDI	DIFFERENCE HDI-MIMIC1	DIFFERENCE HDI-MIMIC2
Argentina	34	55	27	-7	-28
Hungary	21	20	28	7	8
Poland	31	32	29	-2	-3
Chile	38	40	30	-8	-10
Estonia	33	25	31	-2	6
Lithuania	29	27	32	3	5
Slovak Republic	36	34	33	-3	-1
Croatia	24	23	34	10	11
Uruguay	35	31	35	0	4
Costa Rica	41	44	36	-5	-8
Latvia	32	24	37	5	13
Bulgaria	26	17	38	12	21
Trinidad and Tobago	42	45	39	-3	-6
Malaysia	45	59	40	-5	-19
Russian Federation	39	33	41	2	8
Colombia	43	37	42	-1	5
Albania	50	38	43	-7	5
Thailand	53	53	44	-9	-9
Venezuela, RB	54	35	45	-9	10
Ukraine	30	26	46	16	20
Peru	55	46	47	-8	1
Philippines	57	47	48	-9	1
China	47	41	49	2	8
Tunisia	52	48	50	-2	2
Jordan	66	62	51	-15	-11
Sri Lanka	48	65	52	4	-13
Jamaica	46	43	53	7	10
Iran, Islamic Rep.	61	51	54	-7	3
Indonesia	60	58	55	-5	-3
Nicaragua	64	52	56	-8	4
Bolivia	44	49	57	13	8
Guatemala	56	42	58	2	16
South Africa	51	63	59	8	-4
Morocco	49	60	60	11	0
India	58	57	61	3	4
Pakistan	65	54	62	-3	8
Nepal	62	66	63	1	-3
Ghana	68	64	64	-4	0
Uganda	59	67	65	6	-2
Madagascar	40	56	66	26	10
Kenya	67	68	67	0	-1
Cote d'Ivoire	63	50	68	5	18

Considering only the potential social spending (MIMIC1), the biggest negative differences come from Australia, Canada, New Zealand, Korea, Jordan, Thailand and Venezuela. These countries are doing better than their potential. Meanwhile, the biggest positive differences come from Austria, Bolivia, Croatia, Ukraine, Morocco and Madagascar. These countries are not functioning at their best level.

8. Conclusions

In this paper a latent variable methodology was applied to a social policy context. The aims of this dissertation were to provide an accurate theoretical framework in order to obtain scores of potential social policy, which make possible the differentiation of "actual policy" from "feasible policy" (capability), and also to calculate individual effects (random intercepts) for each country given the structure of the data.

The model appears as an appropriate choice to this particular context, showing that economic, social, demographic and political variables influence the level of social policy that a country can provide.

In the social spending dimension there were no problems during the estimation of the model, while some inconveniences were found in the social security dimension du to the small within variation and the nature of the data.

This paper shows data limitations when the number of missing values is important. Because of this problem countries and years have been excluded of the dataset before and during the estimations. In spite of this, some ranking tables were built with a reasonable number of countries that allow comparisons over time and with other indices such as HDI. It revealed that some countries do not perform at their potential while some others do better taking into account their situation, which was one of the objectives of this dissertation.

Finally, for future research it will be interesting to fill missing values of the database, to find other pertinent variables that could be add to the empirical model, to analyze more social policy dimensions and to look for economic explanations to the ranking variations.

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