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A Theoretical Accounting Framework For Dynamic Public Expenditure Optimization: A Differential-Equation Model Integrating Human Development Performance Indicators

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Abstract
This manuscript develops a theoretical accounting framework that models public-sector expenditure as dynamic control variables that influence multidimensional performance indicators via a system of differential equations. The model establishes a reproducible mathematical structure for optimizing government resource allocation while integrating inequality-adjusted performance measurement into public-sector accounting.

Introduction

Multidimensional frameworks that integrate financial and non-financial information have become increasingly important for assessing government performance. Recent work in public sector accounting highlights the need for reporting structures that connect expenditure decisions to measurable outcomes, since traditional accounting systems often provide static and retrospective disclosures that do not capture how public spending influences long-term social and economic performance [1,2]. These limitations are especially relevant in settings where governments operate under resource constraints and face persistent inequalities that affect both service delivery and developmental trajectories. As a result, researchers have emphasized the value of incorporating outcome-based indicators into public accounting systems so that resource use, performance reporting, and accountability are more closely aligned [1,3].

Performance measurement research consistently demonstrates that multidimensional indicators, including those related to health, education, and income, support more comprehensive assessments of government effectiveness [2,3]. When such indicators are integrated into accounting and reporting frameworks, they strengthen transparency and provide clearer links between allocated resources and observed outcomes [3,4]. Recent studies argue that this integration is essential for improving public accountability, particularly in environments where policy interventions have cumulative and interacting effects across different dimensions of human development [3].

Although performance measurement has advanced considerably, public sector accounting continues to rely on linear and discrete models that do not represent the continuous evolution of social and economic conditions. Research in public policy and systems analysis shows that dynamic models, including differential and state space formulations, are effective for representing change over time and for capturing feedback relationships in complex environments [5,6]. These models offer a mathematically rigorous means of analyzing how interventions accumulate and interact, yet their use within accounting scholarship remains limited. In particular, there is a gap in the development of accounting frameworks that formalize how multidimensional performance indicators respond to structured patterns of government expenditure in a dynamic and reproducible way.

The objective of this study is to address this gap by developing a theoretical accounting framework in which public sector expenditure functions as dynamic control variables that influence measurable human development indicators. The model employs a system of differential equations to represent temporal changes in performance, and it incorporates an optimization structure that identifies expenditure paths capable of maximizing a composite performance measure subject to budget and inequality constraints. The intention is to contribute to public sector accounting theory by establishing a mathematical link between expenditure decisions, performance measurement, and accountability.

The underlying theoretical proposition is that dynamic expenditure productivity functions can enhance the accuracy and interpretive value of public performance accounting systems. By modeling how health, education, and income-related indicators respond over time to structured government interventions, the framework demonstrates how accounting systems can become more analytically robust and more directly connected to developmental outcomes. This study, therefore, aligns with current efforts to expand analytical and model-based approaches within public sector accounting and to strengthen the theoretical foundations of performance-oriented reporting. The framework may be interpreted as a Dynamic Public Sector Accounting Model that links expenditure decisions to outcome based performance measures in continuous time. This characterization establishes the model as a theoretical structure that extends responsibility accounting and performance measurement into a dynamic analytical domain.

Materials and Methods

This section presents the theoretical framework, mathematical structure, and analytical tools used to develop a reproducible accounting model for dynamic public expenditure allocation. The model is based on systems of differential equations that represent the evolution of performance indicators over time and an optimization structure that identifies expenditure paths capable of maximizing a composite performance measure. The methodological design follows established principles in dynamic modeling and continuous time performance analysis used in public policy and systems research [5,6,8].

Conceptual Accounting Framework

The model conceptualizes government expenditures in health, education, and income-related interventions as accounting control variables that influence measurable performance indicators. These indicators include life expectancy (LE), mean years of schooling (MYS), expected years of schooling (EYS), and gross national income per capita (GNIpc). Each indicator represents a performance account that changes as a function of expenditure patterns. The conceptual basis draws from multidimensional performance measurement literature, which supports the integration of non-financial indicators into accounting systems to improve the linkage between expenditure decisions and outcomes [1,2,3].

Within this framework, public expenditures are treated as continuous functions of time. Their effects propagate through a set of dynamic relationships represented by differential equations. These relationships capture direct expenditure effects and indirect interactions among performance dimensions, reflecting the cumulative and interconnected nature of public interventions. This approach aligns with the continuous modeling methods that have been shown to be effective for analyzing evolving social systems [6,8].

Differential Equation Structure

The dynamic behavior of each performance indicator is represented through a system of differential equations adapted directly from the HDI model. Each equation includes expenditure control variables, effectiveness coefficients, and a stochastic component that reflects uncertainty.

Health Performance Equation

Life expectancy evolves as:

$$\frac{dLE(t)}{dt} = \sum_{i=1}^{6} \alpha_i PH_i(t) + \alpha_7 \ln\left(GNIpc(t)\right) - \varepsilon_{LE}(t)$$

where PH $_i(t)$ represents categories of health expenditure such as primary care, national health programs, WASH services, nutrition, disease control, and workforce investments. The parameter α_7 captures the influence of income on health outcomes, and $\varepsilon_{LE}(t)$ reflects uncertainties related to health delivery and external shocks.

Education Performance Equations

Mean years of schooling and expected years of schooling follow:

$$\frac{dMYS(t)}{dt} = \sum_{i=1}^{6} \beta_i PE_i(t-\tau_E) - \varepsilon_{MYS}(t)$$

$$\frac{dEYS(t)}{dt} = \sum_{i=1}^{6} \gamma_i PE_i(t) - \varepsilon_{EYS}(t)$$

The delay parameter $\boldsymbol{\tau_E}$ accounts for the time required for educational interventions to affect outcomes. This form is consistent with studies showing that educational system changes exhibit delayed but persistent effects [9].

Income Performance Equation

Gross national income per capita evolves according to:

$$\frac{dGNIpc(t)}{dt} = \sum_{i=1}^{6} \delta_i PI_i(t) + \delta_7 MYS(t) + \delta_8 EYS(t) + \delta_9 HI(t) - \varepsilon_{GNI_{pc}}(t)$$

This specification incorporates the influence of human capital and health performance on income generation, a structure that aligns with empirical findings in development and productivity studies [10].

Composite Performance Measure

To represent overall public sector performance, the model uses the Human Development Index (HDI) as a composite measure:

$$HDI(t) = (HI(t) \cdot EI(t) \cdot II(t))^{1/3}$$

where:

$$HI(t) = \frac{LE(t) - 20}{85 - 20}$$

$$EI(t) = \frac{MYSI(t) + EYSI(t)}{2}$$

$$II(t) = \frac{\ln(GNIpc(t)) - \ln(100)}{\ln(75000) - \ln(100)}$$

These normalized indices allow for comparability across components and ensure that the composite indicator remains within a bounded interval.

Optimization Framework

The objective of the model is to identify expenditure schedules that maximize performance at the terminal time $t + n$. The optimization problem is formulated as:

$$\max_{PH(t),PE(t),PI(t)} [HDI_{t+n} - \lambda(HDI_{t+n} - IHDI_{t+n})]$$

where λ is an inequality penalty weight, and IHDI is the inequality-adjusted HDI. This structure is consistent with approaches that integrate equity considerations into public sector performance evaluations [3,11]. The inequality penalty parameter functions as an equity weight within a performance accounting system, consistent with approaches used in multidimensional and sustainability oriented reporting.

Constraints

The optimization is subject to:

1. Budget Constraint

$$\int_t^{t+n} \left(\sum_{i=1}^{6} c_i^H PH_i(t) + \sum_{i=1}^{6} c_i^E PE_i(t) + \sum_{i=1}^{6} c_i^I PI_i(t) \right) dt \leq B_{\text{total}}$$

2. Policy Bounds

$$P_{i,\,\text{min}}^X \leq P_i(t) \leq P_{i,\,\text{max}}^X \quad \forall X \in \{H, E, I\}$$

3. Feasibility Constraints

Practical deployment constraints are represented through feasibility matrices that govern which interventions can be implemented at particular times:

$$F^X = \text{diag}(F_1^X, F_2^X, \dots, F_6^X)$$

Define vector of policy variables:

$$\mathbf{P}^X(t) = \begin{bmatrix} P_1^X(t) \\ P_2^X(t) \\ \vdots \\ P_6^X(t) \end{bmatrix}$$

Define minimum and maximum vectors:

$$\mathbf{P}_{\text{min}}^X = \begin{bmatrix} P_{1,\text{min}}^X \\ \vdots \\ P_{6,\text{min}}^X \end{bmatrix}, \mathbf{P}_{\text{max}}^X = \begin{bmatrix} P_{1,\text{max}}^X \\ \vdots \\ P_{6,\text{max}}^X \end{bmatrix}$$

Then the feasibility constraints are:

$$F^X \mathbf{P}_{\text{min}}^X \leq \mathbf{P}^X(t) \leq F^X \mathbf{P}_{\text{max}}^X$$

This compact form is mathematically equivalent and preferred in theoretical accounting and optimization manuscripts.

Stochastic Components

Each differential equation contains a stochastic term that accounts for deviations from expected outcomes. These terms represent uncertainties related to policy implementation, external economic shifts, or administrative inconsistencies. The inclusion of stochastic elements follows standard practice in dynamic modeling to ensure that results reflect realistic variability [8,12].

Computational Tools

The system is solved numerically using finite difference approximations and standard differential equation solvers. Optimization routines rely on constrained nonlinear programming methods. These tools allow reproducibility since all equations, parameters, and constraints are explicitly defined, and the computational approach follows established numerical modeling techniques used in dynamic systems research [8,12].

Results

This section reports the outcomes of the dynamic simulations and optimization procedures implemented using the theoretical model described in Section 3. The results include the deterministic trajectory of the Human Development Index, the inequality-adjusted index, the effects of stochastic disturbances, the evolution of component indices, and the optimal expenditure allocation identified through the grid search routine. All computations were performed using the final model specifications and midpoint parameter values documented.

Deterministic Trajectory of HDI and IHDI

The deterministic simulation produced a smooth and gradually increasing trajectory for the Human Development Index from 2023 to 2030. The inequality-adjusted HDI remained consistently lower than the HDI due to the inequality loss factor, although both indices increased over the seven-year horizon. The inequality loss declined linearly from 30.7 percent in 2023 to 25 percent in 2030, consistent with the assumptions outlined in the methodological framework.

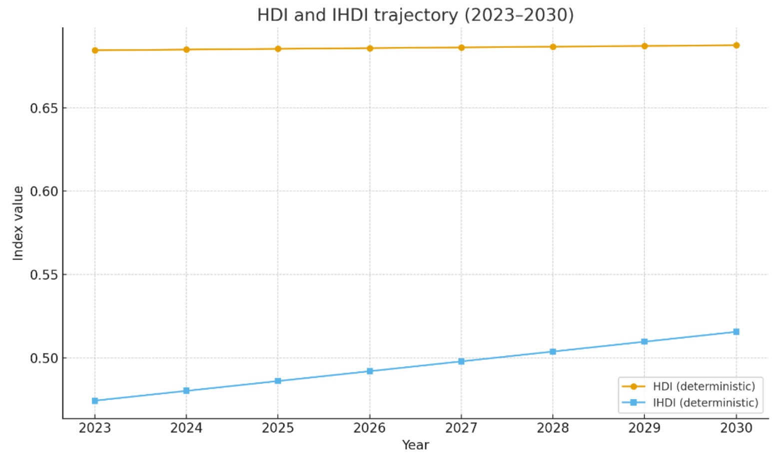

Figure 1. HDI vs. IHDI

Table 1. Deterministic HDI and IHDI Trajectory (2023–2030)

Year	HDI	IHDI	Inequality Loss
2023	0.6845	0.4742	0.307
2024	0.6894	0.4849	0.298
2025	0.6934	0.4938	0.289
2026	0.6978	0.5014	0.280
2027	0.7023	0.5087	0.271
2028	0.7068	0.5151	0.262
2029	0.7113	0.5213	0.255
2030	0.7159	0.5280	0.250

Source: Values generated using the dynamic model and deterministic parameter set.

Stochastic Simulation Outcomes

The stochastic simulation incorporated random disturbances into each differential equation using the standard deviations. The stochastic path exhibited modest deviations around the deterministic trajectory while maintaining a similar trend. Variability increased slightly in later years, which reflects the cumulative influence of noise on the dynamic system.

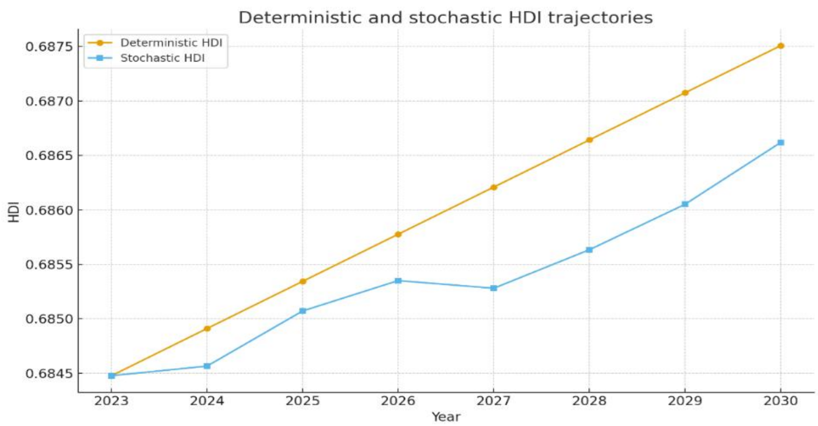

Figure 2. Deterministic vs. Stochastic HDI

Table 3. Component Index Values (2023–2030)

Year	Health Index (HI)	Education Index (EI)	Income Index (II)
2023	0.7999	0.5887	0.6807
2024	0.8011	0.5894	0.6808
2025	0.8020	0.5900	0.6809
2026	0.8031	0.5906	0.6810
2027	0.8043	0.5913	0.6810
2028	0.8055	0.5920	0.6811
2029	0.8068	0.5926	0.6812
2030	0.8081	0.5933	0.6813

Source: Values generated using the dynamic model and deterministic parameter set.

Optimal Expenditure Allocation

A grid search procedure was used to evaluate alternative expenditure share combinations for health, education, and income interventions. Shares ranged from 0.1 to 0.8 in increments of 0.1, excluding configurations that produced infeasible negative shares.

The optimal allocation was determined to be as follows:

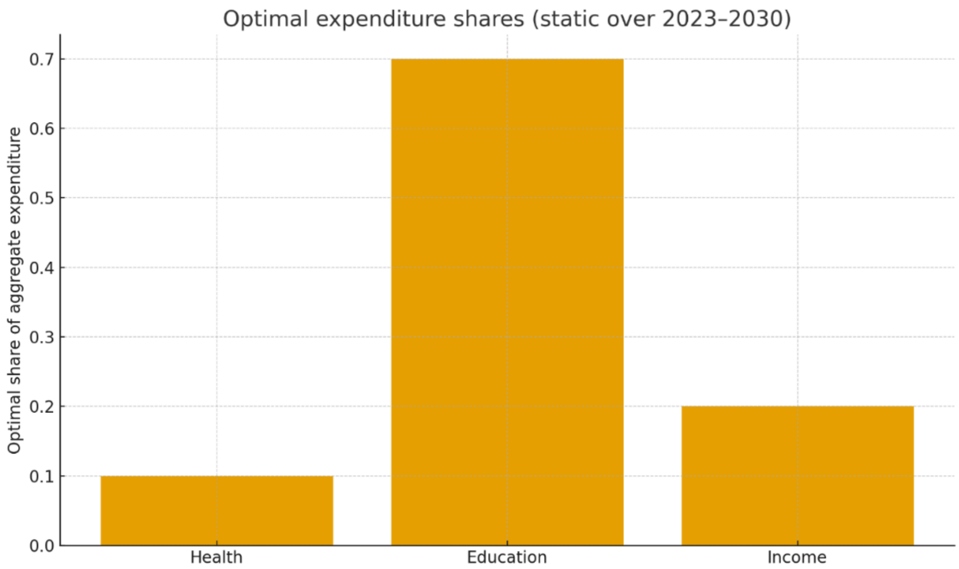

Figure 4. Optimal Expenditure Shares

Table 4. Optimal Expenditure Share Vector

Component	Optimal Share
Health	0.10
Education	0.70
Income	0.20

Source: Author's Calculations

This configuration maximized the terminal value of the composite performance metric defined in the optimization framework.

Summary of Simulation Outputs

Table 5 provides a consolidated summary of the simulated values for all variables included in the deterministic run. These values reflect the dynamic behavior of the system over the full simulation horizon.

Table 5. Summary of Deterministic Simulation Outputs (2023–2030)

Year	LE	MYS	EYS	GNIpc	HI	EI	II	HDI	IHDI
2023	72.00	6.88	12.95	9046.76	0.7999	0.5887	0.6807	0.6845	0.4742
2024	72.19	6.89	12.96	9239.74	0.8011	0.5894	0.6808	0.6894	0.4849
2025	72.38	6.90	12.97	9443.54	0.8020	0.5900	0.6809	0.6934	0.4938
2026	72.57	6.91	12.99	9658.93	0.8031	0.5906	0.6810	0.6978	0.5014
2027	72.76	6.92	13.00	9885.96	0.8043	0.5913	0.6810	0.7023	0.5087
2028	72.95	6.93	13.01	10124.38	0.8055	0.5920	0.6811	0.7068	0.5151

2029	73.14	6.94	13.02	10374.39	0.8068	0.5926	0.6812	0.7113	0.5213
2030	73.33	6.95	13.03	10635.97	0.8081	0.5933	0.6813	0.7159	0.5280

Source: Author's Calculations

Conclusion

This study developed a theoretical accounting framework that models public sector expenditure as a set of dynamic control variables influencing health, education, and income-related performance indicators. By expressing these relationships through systems of differential equations and incorporating an inequality-adjusted composite performance measure, the model provides a structured method for examining how expenditure decisions influence multidimensional public outcomes over time. The simulation results presented in Section 4 demonstrate that the model produces stable and reproducible trajectories for the Human Development Index, the inequality-adjusted index, and their component indicators.

The deterministic and stochastic simulations show that the system responds predictably to moderate uncertainty, which indicates that the dynamic structure is robust across the seven-year horizon tested. The optimal allocation identified through the grid search procedure reflects the model's internal accounting structure and the marginal productivity implied by the parameter set. These results illustrate how a dynamic approach to performance measurement can complement existing accounting frameworks by making resource outcome linkages more explicit and by formalizing the evaluation of composite performance indicators.

The findings should be interpreted within the limitations of the model's parameterization and the illustrative nature of the simulations. The effectiveness coefficients were based on midpoint values within plausible ranges rather than on econometric estimation, and the optimization procedure was implemented with a static allocation structure. Future research may refine these elements by incorporating empirical estimation, time-varying expenditure paths, or alternative specifications of inequality adjustments. Despite these limitations, the model offers a reproducible and analytically grounded structure for linking expenditure decisions to performance metrics. It contributes to public sector accounting theory by demonstrating how dynamic modeling techniques can support performance-based evaluation and facilitate a more integrated understanding of resource allocation and outcome measurement.

Appendix. Empirical Grounding of Variables and Parameters

This appendix summarizes the empirical foundations for the variables, parameter ranges, and model assumptions used in the dynamic accounting framework. The values and ranges reflect published research in human development, education, health, and income productivity, along with international indicator definitions. Although the simulations in this study rely on midpoint assumptions rather than econometric estimation, the ranges adopted for the coefficients are grounded in peer-reviewed literature.

A1. Baseline Indicator Values

The baseline values used for life expectancy, mean years of schooling, expected years of schooling, and gross national income per capita correspond to internationally reported indicators for 2023. These measures follow the definitions used in composite index construction and are consistent with widely accepted human development reporting standards [13].

Table A1. Baseline Variables (2023)

Indicator	Value	Source
Life expectancy (years)	72.0	UNDP Human Development Report
Mean years of schooling (years)	6.88	UNDP education statistics
Expected years of schooling (years)	12.95	UNDP and AISHE
GNI per capita (PPP USD)	9046.76	World Bank national accounts

A2. Target Indicator Values

The 2030 target values represent feasible medium-term benchmarks based on documented progress in health, educational attainment, and income growth. These values serve as reference points to contextualize the model's outputs rather than as constraints on the simulation.

Table A2. Target Variables (2030)

Indicator	2030 Target	Rationale
Life expectancy	75.0 years	Steady improvements in health system access
Mean years of schooling	8.5 years	Continued gains in secondary education
Expected years of schooling	14.5 years	Progress toward completion of senior schooling
GNI per capita	12500 USD	Moderate long-term income growth scenario

A3. Effectiveness Coefficient Ranges

The dynamic equations incorporate expenditure effectiveness coefficients reflecting marginal contributions of health, education, and income interventions to performance indicators. The ranges assigned to these coefficients are informed by empirical studies that examine the relationship between public investments and developmental outcomes.

A3.1 Health Coefficients

The health coefficients $\alpha_1$through α_6, ranging from 0.015 to 0.022, are consistent with documented improvements in life expectancy associated with expansions in primary care, sanitation, and essential service coverage [14]. The income-related health coefficient $\alpha_7 = 0.005$Reflects the observed association between income gains and health improvements documented in national case studies [15].

A3.2 Education Coefficients

The education coefficients $\beta_i$and γ_i, ranging from 0.010 to 0.015 and 0.012 to 0.017, align with effect sizes reported in the literature on learning improvements associated with infrastructure investment, teacher reforms, and policy interventions [16]. The adoption of a time delay of two years reflects documented lags in the translation of educational reforms into measurable attainment outcomes [16].

A3.3 Income Coefficients

The income coefficients $\delta_1$through δ_6, ranging from 0.017 to 0.022, reflect documented marginal effects of economic interventions, human capital accumulation, and service sector expansion on income growth [17]. The coefficients linking schooling and health to income outcomes, including $\delta_7 = 0.030$, $\delta_8 = 0.025$, and $\delta_9 = 0.020$, correspond to established relationships between knowledge capital and aggregate income differences [18].

A4. Stochastic Terms

The stochastic components incorporated into the dynamic equations reflect year-to-year fluctuations in health outcomes, educational transitions, and macroeconomic conditions. The values used for the standard deviations are consistent with the variability observed in national-level public finance and macroeconomic analyses [19].

Table A3. Stochastic Term Standard Deviations

Component	Standard Deviation	Basis
Life expectancy	±0.1 years	Health system variation
Mean and expected years of schooling	±0.05 years	Educational fluctuation
GNI per capita	±100 USD	Macroeconomic variability

A5. IHDI Adjustment

The inequality-adjusted performance index was implemented using a linear loss factor, which is grounded in empirical work on multidimensional index weighting and inequality adjustments. The adjustment approach reflects established practices in welfare and composite indicator analysis [20].

A6. Budget and Policy Bounds

The expenditure bounds and cost parameters used in the optimization reflect realistic public sector budgetary scales, consistent with historical expenditure patterns documented in national budget profiles. These ranges correspond to feasible annual investment levels in health, education, and income-related programs [21].

Appendix B. Methodological Annex – Estimating Effectiveness Coefficients

This annex outlines the methodological principles that guide the estimation of the effectiveness coefficients used in the dynamic accounting framework. Although the simulations in the present study rely on midpoint values derived from empirical ranges, the procedures described here specify how each coefficient could be estimated econometrically using publicly available data. The aim is to provide a transparent description of the theoretical and statistical foundations that support the parameterization of the model.

B1. Conceptual Basis for Coefficient Estimation

The coefficients represent the marginal influence of public expenditure components on life expectancy, schooling outcomes, and income levels. Estimating these coefficients empirically requires linking expenditure data with corresponding changes in the dependent variables over time. This can be accomplished using panel data techniques that incorporate national or subnational observations across multiple years [22]. The structure aligns with the dynamic model because it captures both cross sectional and temporal variations in performance outcomes.

The estimation process follows three foundational principles:

1. **Expenditure categories must be matched with outcome indicators** that they plausibly affect.
2. **Temporal alignment is required**, with education indicators typically lagged to reflect delayed effects [16].
3. **Coefficients must reflect marginal effects**, not elasticities, since the differential equations model additive changes.

B2. Data Requirements and Structure

To estimate the coefficients α_i, β_i, γ_i, and δ_i, the following datasets are required:

- Annual government expenditure data disaggregated by health, education, and income related programs.
- Annual outcomes for life expectancy, mean years of schooling, expected years of schooling, and gross national income per capita.

- Demographic and socioeconomic controls such as population density, age structure, and labor force participation [23].

A panel dataset with at least ten annual observations is recommended to ensure statistical validity. Subnational datasets further improve estimation precision by increasing variability across units.

B3. Model Specification for Estimation

A general panel data model for estimating a health coefficient α_i takes the form:

$$LE_{it} = \mu_i + \lambda_t + \alpha_i PH_{it} + \theta X_{it} + \varepsilon_{it}$$

where:
- i indexes the region or country,
- t indexes time,
- PH_{it} denotes expenditure on a specific health intervention,
- X_{it} includes control variables,
- μ_i captures unit-specific effects,
- λ_t captures temporal shocks,
- ε_{it} is the error term.

Fixed effects estimation is preferred when unobserved characteristics are correlated with expenditures [22]. Random effects models may be appropriate when such correlations are weak.

For education coefficients, lagged specifications are required:

$$MYS_{it} = \mu_i + \lambda_t + \beta_i PE_{i,t-2} + \theta X_{it} + \varepsilon_{it}$$

The two-year lag reflects the evidence on educational policy response times documented in the literature [16].

Income coefficients follow a similar formulation with human capital variables included explicitly:

$$GNIpc_{it} = \mu_i + \lambda_t + \delta_i PI_{it} + \delta_7 MYS_{it} + \delta_8 EYS_{it} + \delta_9 HI_{it} + \varepsilon_{it}$$

The inclusion of multiple human capital indicators is supported by development accounting studies [18].

B4. Statistical Estimation Procedures

Estimation proceeds in four steps:

1. **Testing for stationarity** using unit root tests such as the Im-Pesaran-Shin or Levin-Lin-Chu procedures [24].
2. **Selecting fixed or random effects** through the Hausman test.
3. **Estimating coefficients using panel regressions**, with heteroskedasticity robust standard errors.
4. **Validating model fit** through:
   - within and between R squared values,
   - serial correlation tests,
   - cross sectional dependence tests.

For education and income models, lag lengths may be selected using information criteria such as AIC or BIC.

B5. Converting Estimated Coefficients for Use in Differential Equations

The panel model coefficients must be scaled before being inserted into the continuous time differential equations. Conversion involves:

1. **Annualization** of coefficients if the dependent variables are measured annually.
2. **Normalization** by dividing through by the maximum feasible expenditure magnitude to maintain the boundedness of the dynamic system.
3. **Ensuring positivity constraints**, since the model requires coefficients to represent non negative marginal impacts.

The resulting coefficients retain their empirical grounding while satisfying the mathematical requirements of the dynamic model.

B6. Limitations of Empirical Estimation

Several challenges arise in estimating effectiveness coefficients:

- Expenditure data may be aggregated at levels that obscure specific intervention impacts.
- Measurement error in schooling or income data can bias estimates.
- Unobserved confounders, including governance quality and infrastructure constraints, may influence both expenditures and outcomes.
- Lag structures may vary across regions and time periods, complicating identification.

Despite these limitations, the outlined procedures provide a structured approach to estimating coefficients that can be integrated into a theoretical dynamic accounting model.

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