Education Attainment, Growth and Poverty Reduction within the MDG Framework: Simulations and Costing for the Peruvian Case

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Abstract

We propose a model that accounts for the potential feedback between schooling performance, the accumulation of human capital and long run GDP growth, and links these results with poverty incidence. Schooling performance, in turn, is affected by the provision of educational services according to results that stem from microeconometric models built using Peruvian data. In this way, public intervention in the educational sector can influence long-run GDP growth and poverty. Our simulation exercise takes into account targets for education indicators and GDP growth itself (as arguments in our planner’s loss function) and provides two conclusions: (i) with additional funds which amount to 1% of GDP each year, public intervention could add, by year 2015, an extra 0.95 and 1.70 percentage points in terms of long-run GDP growth and permanent reduction in poverty incidence, respectively; and (ii) in order to engineer an intervention in the educational sector so as to transfer households the necessary assets to attain a larger income generation potential in the long run, we need to extend the original set of MDG indicators to account for access to higher educational levels besides primary.

Keywords: Millennium Development Goals, education, human capital, GDP growth, poverty, Peru.

JEL Codes: O41, I32, C25, C41, C61.

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1 Introduction and motivation

This project’s main objective is to approximate the potential impact of different scenarios regarding public investment in education over economic growth and poverty incidence. Our analysis is based on the existence of interrelations and synergies between MDG indicators for poverty and education achievement. In this regard, we propose a model that accounts for the potential feedback between schooling performance, the accumulation of human capital and long run GDP growth, and link these results with poverty incidence. Within this framework, we address the issue whether MDG indicators related to education should be restated for the Peruvian case in order to maximize their effect over economic growth and poverty reduction in the long term.

In September 2000, all country members of the United Nations (UN) signed the Millennium Declaration, where they recognized the need to promote a multidimensional vision of development centered in the fulfillment of basic needs with an environmentally sustainable basis. Specifically, they committed to achieve, by the year 2015, a set of goals and targets related to the reduction of poverty, hunger, disease, mortality, illiteracy, environmental degradation and discrimination against women. These are known as the Millennium Development Goals (MDGs).

The wide range of aspects involved in the MDGs, ranging from education to environment and gender equality, reflects the shift towards a broadened concept of poverty (which includes short run poverty symptoms and long run poverty determinants), and the fact that all these issues must be taken care of simultaneously, points out the relevance of promoting a comprehensive approach and a coordinated strategy for reducing poverty around the world.

Thus, MDGs can be viewed as an important step towards a consensus regarding the minimum set of arguments that a social planner’s loss function must include, specially when considering inter-temporal difficult choices between short term poverty alleviation and long term poverty reduction. They have contributed to the debate regarding the multidimensional
aspects of poverty and, in terms of policy analysis and design, made explicit the need for a systemic approach.

MDG assessment has been usually conducted on a sectorial basis, estimating the future path of each indicator as a function of its past evolution, or via structural models that account for a limited set of determinants, typically taking other MDG indicators as given. Thus, MDG prediction and costing can be biased because of the failure to consider the interactions among policy interventions and indicators.

The rest of the document is organized as follows. Section 2 provides a detailed description of the methodology undertaken for this study. The third section describes empirical results related to a simulation exercise which takes into account targets for education indicators and/or GDP growth itself (as arguments in our planner’s loss function) and assesses the potential impact of reaching these targets in terms of the accumulation of human capital, aggregate GDP growth and poverty incidence. The fourth and final section summarizes our conclusions.

2 Methodology

The model proposed involves four different blocks: (i) a macro block (which connects educational attainment with aggregate GDP growth via the accumulation of human capital); (ii) an education block (which involves specific functional forms relating education indicators with a set of determinants based on results that stem from micro-econometric estimations using Peruvian household data); (iii) a poverty block (which links GDP growth and changes in the Gini coefficient with the incidence of monetary poverty); and (iv) a costing and resource constraint block (which specifies cost functions for specific policy interventions identified in (ii), and links these to a planner budget constraint).

These four blocks are integrated in order to provide the system of constraints faced by the planner when trying to minimize her loss function. This loss function LF[·], in turn, depends
on the distance between each target value and the level attained by the indicator at the end of the planning period (year 2015).

For a general discussion, let us assume that we have exogenous targets ($T_j$) for two groups of MDG indicators ($I_{jt}$; $j = 1, 2$) related to monetary poverty and education, respectively. Period ($t$) value for the incidence of monetary poverty is assumed to be a function of per-capita GDP growth ($y_{t}$) and the percentage change in the Gini coefficient ($\alpha_t$): $I_{t} = I_{t} \left[ y_{t}, \alpha_t \right]$.

Period ($t$) values for the education MDG indicators, on the other hand, are given by: $I_{2t} = I_{2t} \left[ x_{it}, y_{t-1}, y_{t-1}, x_{it} \right]$, where the specific form of the function $I_{j} \left[ \cdot \right]$ will depend on the results of the micro-econometric modeling exercise. In the expression above, $x_{it}$ refers to period ($t$) value of policy variable ($i$).

Given the above (and for $t = 0, \ldots, T$), the proposed optimization problem can be summarized as follows.

Choose ($x_{it}$) to

\[
\text{Min} \quad LF \left[ \text{GAP}_j \right]
\]

\[
\text{GAP}_j = \frac{\text{abs}(T_j - I_{jt})}{T_j}; \quad j = 1, 2
\]

subject to:

(i) Macro block

Where per capita GDP growth is a function of the population growth rate ($\gamma_{N, t}$), the rate of growth of technology ($\gamma_{A, t}$) (both exogenous), and the rate of growth of human capital ($\gamma_{H, t}$). The latter, in turn, depends on the value attained by the indicators related to education ($I_{2t}$).

\[
(1) \quad \gamma_{y, t} = \gamma_y \left[ \gamma_{H, t}, \gamma_{N, t}, \gamma_{A, t} \right]
\]

\[
(2) \quad \gamma_{H, t} = \gamma_H \left[ I_{2t}, \cdot \right]
\]
(ii) Education block
Where the value of each MDG indicator depends on per-capita GDP growth, and the value attained by each policy variable, according to the functional forms and parameter estimates given by the micro-econometric modeling exercise.

\[ I_{2t} = I_2\left[ x_{it}, \gamma_{y,t-1}, \right] \]

(iii) Poverty block
Where the incidence of monetary poverty is a function of the growth rate of per-capita income and the percentage change in the Gini coefficient.

\[ I_{1,t} = I_1\left[ \gamma_{y,t}, \alpha_t \right] \]

(iv) Costing and resource constraint block
Where total costs related to specific policy interventions in period \( t \) (\( TC_t \)) are a function of the values attained by policy variables. Each period, these total costs must be such that the fiscal deficit (equivalent to the difference in the stock of public debt, \( D_t - D_{t-1} \)) does not exceed a percentage (\( \lambda \)) of aggregate GDP, for a given interest rate (\( r \)) and given levels of recurrent fiscal expenditure (\( G_t \)) and revenues (\( R_t \)).

\[ TC_t = TC[x_{it}, \cdots] \]

\[ \gamma_t = \left( x_{it} / x_{i0} \right)^{1/T} - 1; \quad x_{it} = x_{i0}^{(\gamma_t)} \]

\[ D_t = (1 + r)D_{t-1} + G_t + TC_t - R_t \]

\[ D_t - D_{t-1} \leq \lambda Y_t \]

\[ Y_t = Y_{t-1}(1 + \gamma_{y,t} + \nabla_t) \]

The system described above highlights the main interactions and feedbacks we intend to capture. In particular, we allow for a feedback between education indicators and aggregate GDP growth which will, in turn, lead to further improvements in education and poverty MDG indicators.
In what follows, we present a detailed description of the analytical derivation of functional forms related to each of the four blocks involved in the aggregate model.

2.1 The Macro Block

One of the main objectives of this paper is to build an integrated model that accounts for the feedback between schooling performance, the accumulation of human capital and long run GDP growth. Following Lucas (1988), our analytical framework is based on a model where date t aggregate production ($Y_t$) is given by the combination of physical ($K_t$) and human ($H_{yt}$) capital via a Cobb-Douglas technology:

$$Y_t = A_t K_t^\beta H_{yt}^{\beta(1-\beta)}$$  \hspace{1cm} (10)

In the expression above, $H_{yt}$ is the stock of human capital devoted to production (labor force adjusted for productivity), and this is assumed to be equal to a proportion ($\mu_y$) of the total stock of human capital ($H$). The remaining proportion ($H_h = \mu_h H$) is devoted to the accumulation of more human capital according to:

$$\dot{H} = BH_h - \delta H = B\mu_h H - \delta H$$  \hspace{1cm} (11)

where $B$ is the parameter describing the technology of the educational sector (the rate at which human capital is transformed into more human capital) and $\delta$ is the depreciation rate of human capital. Thus, human capital growth ($\gamma_H$) is given by:

$$\gamma_H = B\mu_h - \delta$$  \hspace{1cm} (12)

Given the above, our objective is to link this growth rate with observed enrolment and graduation rates in the different educational levels. In fact, these rates will influence the technology of the education sector, so changes in $\gamma_H$ will be engineered through changes in
B. In this way, and if these rates can be affected by the provision of public services, our model will capture the planner’s potential ability to influence long run GDP growth by fostering the accumulation of human capital.

At this point, it is worth mentioning that the steady state (SS) solution for Lucas’ model implies a balanced growth path where $\gamma^ss_k = \gamma^ss_h$. This growth rate, in turn, depends on the parameter governing the technology of the educational sector (B), the depreciation rate of human capital and parameters defining consumer preferences (the inter-temporal discount rate and risk aversion). In order to fully account for the evolution of $\gamma_h$, we will rely on this steady state solution and, since our simulation exercise is based on introducing changes in parameter B, our assumption is that planner’s intervention will change the economy’s steady state GDP growth rate via the provision of additional educational services. Thus, following (1) and introducing the result $\gamma_k = \gamma_h$, we will assume that long run GDP will grow at a rate given by:

$$\gamma_Y = \gamma_k + \gamma_h$$

(13)

where the rate of growth of technology was obtained via the growth accounting exercise described in Appendix 1.

Our specification

We will extend Lucas’ model (1988) to consider the existence of three different educational levels (primary, secondary and tertiary). In order to do this we propose a Barro-Lee (2000) type of human capital aggregation: the stock of human capital devoted to production ($H_Y$) will equal the number of individuals in the labor force with each educational level, adjusted by their corresponding productivity ($\lambda_{yi}, i = 1, 2, 3$). Similarly, the stock of human capital devoted to the accumulation of more human capital ($H_i$) will equal the number of individuals enrolled in each educational level adjusted by their corresponding productivity ($\lambda_{hi}, i = 1, 2, 3$).
In each case, and considering that labor markets in Latin America exhibit non-linear returns to education (Bourguignon et al., 2005), we define productivity in terms of market-based returns for each educational cycle (see Appendix 1) instead of using the number of schooling years as originally proposed by Barro and Lee.

As already mentioned, our objective is to link human capital accumulation with enrolment and graduation rates. For this, let us define:

- \( E_t \) equals the number of 6 year-olds in period \( t \).
- \( g_{t,\text{entry}} \) equals the period \( t \) probability of enrolling in primary education at normative age (6 year-olds).
- \( g_{t,\text{gradprim}} \) equals the period \( t \) probability of graduating within the primary education cycle.
- \( g_{t,\text{grdcont sec}} \) equals the period \( t \) probability of enrolling in secondary education, given that the primary cycle has been completed.
- \( g_{t,\text{grad sec}} \) equals the period \( t \) probability of graduating within the secondary education cycle.
- \( g_{t,\text{grdcont sup}} \) equals the period \( t \) probability of enrolling in tertiary education, given that the secondary cycle has been completed.
- \( g_{t,\text{grad sup}} \) equals the period \( t \) probability of graduating within the tertiary education cycle.
- \( n_i \) equals the number of grades within educational cycle “\( i \)”, \( i=\text{prim} \) (primary), \( \text{sec} \) (secondary), \( \text{sup} \) (tertiary). For simplicity, we will assume that students are evenly distributed among grades within each educational cycle.

\[
\begin{align*}
H_Y &= H_{Y0} + \lambda_{Y1} H_{Y1} + \lambda_{Y2} H_{Y2} + \lambda_{Y3} H_{Y3} \\
H_H &= \lambda_{H1} H_{H1} + \lambda_{H2} H_{H2} + \lambda_{H3} H_{H3} \\
H &= H_Y + H_H \\
\mu_{hi} &= \frac{\lambda_{hi} H_{hi}}{H}, \quad i = 1, 2, 3. \\
\mu_{yi} &= \frac{\lambda_{yi} H_{yi}}{H}, \quad i = 1, 2, 3.
\end{align*}
\]
Given the above, the following equations define the number of individuals in the labor force and enrolled in each educational level.

\[ Y_{0,t} = (1 - \delta)Y_{0,t-1} + (1 - g_{\text{entry},t})E_6_t \]

(15a)

where the stock of human capital with no education devoted to production is equal to last period’s remaining stock (considering a depreciation rate of \( \delta \)) plus year t six year-olds that do not enroll in primary education. Despite that the official working age in Peru is fourteen, this formulation not only guarantees simplicity but also accounts for the fact that those children who do not attend school are typically providing labor services to their households, specially in rural areas.

\[ H_{1,t} = (1 - \delta - \frac{\text{grd}_{\text{prim},t-1}}{\text{n}_{\text{prim}}})H_{1,t-1} + (g_{\text{entry},t})E_6_t \]

(15b)

where the stock of human capital with primary education devoted to further human capital accumulation is equal to the last period’s remaining stock of children in primary school (those surviving minus those who graduated from primary cycle) plus period t six year-olds enrolling in primary. Following the assumption that students are evenly distributed among grades within each educational cycle, \( \frac{H_{1,t-1}}{\text{n}_{\text{prim}}} \) denotes the number of students in the last grade of primary education.

The remaining equations in this group follow a similar logic.

\[ H_{2,t} = H_{2,t-1} (1 - \delta - \frac{\text{grd}_{\text{sec},t-1}}{\text{n}_{\text{sec}}}) + H_{1,t-1} \left[ \frac{\text{grd}_{\text{prim},t-1}}{\text{n}_{\text{prim}}} \right] \text{grd}_{\text{cont sec},t} \]

(15c)

\[ H_{3,t} = H_{3,t-1} (1 - \delta - \frac{\text{grd}_{\text{sup},t-1}}{\text{n}_{\text{sup}}}) + H_{2,t-1} \left[ \frac{\text{grd}_{\text{sec},t-1}}{\text{n}_{\text{sec}}} \right] \text{grd}_{\text{cont sup},t} \]
If we replace the above relations in (14) and after some algebraic manipulations, we obtain:

\[ H_{t+1} = H_t(1 - \delta) + E6_t + (\lambda_{hi} - 1)E6_t(g1entry_t) + \ldots \]

\[ ... + H_{hi,t-1} \left[ \frac{\text{grdprim}_{t-1}}{n_{prim}} \right] [(\lambda_{hi} - \lambda_{hi})\text{grdcont sec}_i + (\lambda_{y1} - \lambda_{hi})(1 - \text{grdcont sec}_i)] + \ldots \]

\[ ... + H_{hi2,t-1} \left[ \frac{\text{grd sec}_{t-1}}{n_{sec}} \right] [(\lambda_{hi} - \lambda_{hi})\text{grdcont sup}_i + (\lambda_{y2} - \lambda_{hi})(1 - \text{grdcont sup}_i)] + \ldots \]

\[ ... + H_{hi3,t-1} \left[ \frac{\text{grd sup}_{t-1}}{n_{sup}} \right] (\lambda_{hi} - \lambda_{hi}) \]

The expression above is our version (in discrete terms) of (11). If we subtract and divide both sides of (16) by \( H_{t-1} \), we finally arrive to an expression for the growth rate of human capital

\[ \gamma_{hi,t} = \frac{(H_t - H_{t-1})}{H_{t-1}} : \]

\[ \gamma_{hi,t} = \left( \frac{E6_t}{H_{t-1}} + \frac{(\lambda_{hi} - 1)E6_t(g1entry_t)}{H_{t-1}} + \right. \]

\[ + \left. \frac{H_{hi,t-1}}{\lambda_{hi}} \left[ \frac{\text{grdprim}_{t-1}}{n_{prim}} \right] [(\lambda_{hi} - \lambda_{hi})\text{grdcont sec}_i + (\lambda_{y1} - \lambda_{hi})(1 - \text{grdcont sec}_i)] + \right. \]

\[ + \left. \frac{H_{hi2,t-1}}{\lambda_{hi2}} \left[ \frac{\text{grd sec}_{t-1}}{n_{sec}} \right] [(\lambda_{hi} - \lambda_{hi})\text{grdcont sup}_i + (\lambda_{y2} - \lambda_{hi})(1 - \text{grdcont sup}_i)] + \right. \]

\[ + \left. \frac{H_{hi3,t-1}}{\lambda_{hi3}} \left[ \frac{\text{grd sup}_{t-1}}{n_{sup}} \right] (\lambda_{hi} - \lambda_{hi}) - \delta \right) \]

Equation (17) is our version of equation (12) above, and it explicitly accounts for the role of enrolment and graduation rates in explaining the behavior of the rate of growth of human capital. In fact, (17) will allow to introduce changes in the technology of the education sector (B) via public interventions aimed at increasing the rate at which individuals progress through this sector. As explained above, B accounts for the rate at which human capital is transformed into more human capital. Since we are considering the existence of three
educational cycles, we have three different technologies within the education sector. Formally:

\[
B_{1,t} = \frac{\text{grdprim}_{t-1}}{n_{\text{prim}}}[\lambda_{H2} - \lambda_{H1}]\text{grdcont sec}_{t} + (\lambda_{V1} - \lambda_{H1})(1 - \text{grdcont sec}_{t})
\]

\[
B_{2,t} = \frac{\text{grdsec}_{t-1}}{n_{\text{sec}}}[\lambda_{H3} - \lambda_{H2}]\text{grdcont sup}_{t} + (\lambda_{V2} - \lambda_{H2})(1 - \text{grdcont sup}_{t})
\]

\[
B_{3,t} = \frac{\text{grdsup}_{t-1}}{n_{\text{sup}}}(\lambda_{V3} - \lambda_{H3})
\]

Clearly, the technology of the educational sector is a function of two elements: (i) enrolment and graduation rates; and (ii) the productivity gains associated to each type of contribution to human capital formation (either by progressing to the next educational level or by entering the labor force with a completed educational cycle).

The last element to be considered in order to fully characterize (17) (and use it to account for the evolution of the rate of growth of human capital), is the proportion of human capital devoted to the education sector. For this, we will rely on the steady state solution of Lucas’ model. Formally:

\[
\mu_{H1,t} = 1 - [(1 - \theta_{1})(B_{1,t} + \delta) + \rho]/[B_{1,t} \theta_{1}]
\]

\[
\mu_{H2,t} = 1 - [(1 - \theta_{2})(B_{2,t} + \delta) + \rho]/[B_{2,t} \theta_{2}]
\]

\[
\mu_{H3,t} = 1 - [(1 - \theta_{3})(B_{3,t} + \delta) + \rho]/[B_{3,t} \theta_{3}]
\]

(19)

where \(\theta\) and \(\rho\) refer to the risk aversion parameter and inter-temporal discount rate, respectively\(^2\).

It is worth mentioning the Lucas’ model only considers one “type” of education and that his representative agent seeks to maximize the discounted path of consumption with preferences defined by a constant relative risk aversion function. There is only one proportion of human capital devoted to education and this is one of the control variables available for the optimization problem. Thus, by using the result provided by Lucas to solve for three different \(\mu_{H1}\)’s (following expression (19) above) we are implicitly assuming that the optimization

\(^2\) Following Dancourt et al. (2004), the inter-temporal discount rate was fixed in 0.02 (2%). Risk aversion parameters, on the other hand, were calibrated to fit (following equation (19)) year 0 values for the proportion of human capital enrolled in each educational level obtained from household survey data (ENAHO 2004).
problem is solved by three different types of agent: (i) one, with no education, who faces the decision of entering the labor force or enrolling and finishing primary education (with transformation technology defined by $B_1$); (ii) a second one, with completed primary education, who faces the decision of entering the labor force or enrolling and finishing secondary education (with transformation technology defined by $B_2$); and (iii) a third one who, being a graduate from secondary education, faces the decision of entering the labor force or enrolling in tertiary education (and be transformed into more human capital according to the technology defined in $B_3$). In fact, these choices are consistent with the conditional nature of the probabilities considered in grdcontsec and grdcontsup (which define the proportion of individuals who progress to the next cycle provided that they have finished the previous one).

2.2 The Education Block

In this block our interest focuses on a set of indicators built to describe the proportion of individuals (from the total population) that exhibit certain qualitative characteristic (MDG indicators regarding education). Moreover, and since the aim of our analysis is to approximate the behavior of this proportion through time, one would expect that the preferred database should explicitly include a time dimension. However, the availability of information typically imposes a trade-off: we usually encounter too few observations for a time series analysis, while household survey data (which substantially increases the number of observations and the variability of covariates through space) typically lack a panel structure. Thus, and if the scarcity of time series information imposes almost no degrees of freedom for estimation, the only practical solution is to rely on cross-sectional household surveys. Obviously, this implies assuming that behavioral patterns captured in year 0 cross-section will not vary significantly through time.

Under this scenario, our estimate of the mean of the dependant variable conditioned on set of covariates is the probability of occurrence of the event under analysis, and the specific functional form for this probability will be given by the type of distribution assumed for the error term. For example, if we assume a logistic distribution and define the vector containing the set of determinants associated to individual (i) as $X_i$, the above will imply:
$$E[y_i|X_i;\psi] = \Pr[y_i = 1|X_i;\psi] = \frac{\exp(X_i,\psi)}{1 + \exp(X_i,\psi)}$$

(20)

The parameters involved ($\psi$) can be estimated with cross-sectional household survey data, and equation (20) can be used to approximate the probability that an individual with characteristics $X_i$ will exhibit the discrete characteristic identified in the dependant variable ($y_i$).

In order to estimate the behavior of MDG indicators through time, and under the assumption that behavioral patterns will remain relatively constant in this dimension, we can rely on the estimated values of $\psi$ and the functional form described in (20) to predict the probability that an average individual will exhibit the characteristic under study in period (t). The probability associated to this “average individual” can be, in turn, directly associated to the proportion of individuals who exhibit the characteristic. For this, we need to evaluate (20) using the mean values (across space) of the set of determinants in period (t) ($\bar{X}_i$). In this way, and for a given set of these mean values, we will be able to predict the indicator’s value in period (t).

$$\text{MDG}_{i,t} = \Pr[y_i = 1|\bar{X}_i;\psi] = \frac{\exp(\bar{X}_i,\psi)}{1 + \exp(\bar{X}_i,\psi)}$$

(21)

Obviously, among the set of determinants $\bar{X}_i$, we will evaluate the role of specific policy variables and relevant controls (such as the mean household expenditure).

On the supply side, our policy variables will account for the provision of specific goods (in this case, educational services). On the other hand, household per capita expenditure will typically control for the private demand. Due to the nature of functional forms relating these determinants to indicators, both policy variables and per capita expenditures will exhibit a diminishing marginal impact over the indicator.
The behavioral assumptions that inspire the class of binary choice models explained earlier are particularly appropriate to capture the cost-benefit analysis that lies behind results regarding education indicators. We can motivate the role of these determinants using the type of extended human capital model proposed in Vos and Ponce (2004) and which stems from the work of Glewwe (1999). Under this theoretical approach, education is viewed as an investment that depends on the costs and benefits associated with enrollment. Costs can be direct (uniforms, books, fees, etc.) or indirect (the opportunity cost—in terms of forgone household income—of sending the child to school), while benefits are mainly related to the accumulation of human capital and its impact on future earnings. In this sense, household conditions, and specially household expenditure, should mainly control for the perceived cost of schooling. Supply side factors, on the other hand, should affect both costs and expected benefits from enrollment. In particular, per capita infrastructure could act as a quality indicator that can be linked to larger expected benefits from schooling.

Enrollment at a particular age in a particular grade can be viewed as the discrete realization of an unobserved latent variable that reflects the net utility associated to schooling. Thus, the probability of observing enrollment corresponds to the probability of a positive net utility which, in turn, depends on a set of determinants linked to household conditions and supply side factors.

Specifically, equation (16) reveals that we require functional forms and parameter estimates relating six different rates to a set of determinants: (i) the probability of enrolling in primary education at normative age (6 year-olds) (g1entry); (ii) the probability of graduating within the primary education cycle (grdprim); (iii) the probability of enrolling in secondary education, given that the primary cycle has been completed (grdcontsec); (iv) the probability of graduating within the secondary education cycle (grdsec); (v) the probability of enrolling in tertiary education, given that the secondary cycle has been completed (grdcontsup); and (vi) the probability of graduating within the tertiary education cycle (grdsup). All our estimates were based on binary logit models. These were applied using cross-sectional information captured in the ENAHO 2003 household survey and administrative records.
Regarding the results presented in Appendix 2, it is worth mentioning that the models that present better fit and more robust elasticities are those that determine the decision to enter each of the three educational levels considered: \textit{g1entry}, \textit{grdcontsec} and \textit{grdcontsup}. As argued in Castro and Yamada (2006), this is due to the fact that initial values of these probabilities are low enough (0.89, 0.93, 0.13, respectively) to allow sufficient variability in the dependant variable. Therefore, these probabilities are still in a point of the logistic function where public intervention could be effective in terms of causing changes in the decision to enter each educational cycle.

The variable that summarizes families’ socio-economic characteristics is the household per-capita expenditure level. It is significant and exhibits the largest elasticity for the decisions of entering primary and tertiary education. In fact, richer families will be in a better position to face the direct and indirect costs related to the decision of sending their children to school.

The variable that reflects public investment in education was built using an interaction between the number of teachers and the number of schools per student. We proposed this variable due to the high degree of complementarity between physical (classrooms) and human capital (teachers) in the provision of better educational services. The results show that this variable is significant when explaining the three probabilities described above.

The model that explains the probability of graduating within each cycle (\textit{grdprim}, \textit{grdsec} and \textit{grdsup}), on the other hand, exhibits a lower fit and weaker elasticities. In fact, and due to the existence of decreasing marginal returns to intervention (captured in our logistic functions), the initial level of these probabilities (around 0.95) are sufficiently high to prevent public intervention from causing a large effect.

At this point, we would like to stress that this work does not pretend to replace proper impact evaluation at the project level when assessing specific interventions in public education. Our intention is to shed light on the detailed mechanics involved throughout the full cycle of educational attainment, the potential priorities to look at for policy guidance from a MDG
perspective, and the aggregate cost for the society in embarking in an active campaign for MDG achievement in education and poverty reduction.

2.3 The Poverty Block

In order to account for the impact of economic growth on individuals’ income and the incidence of monetary poverty (MDG indicator 1), we will rely on the accounting model proposed in ECLAC-IPEA-UNDP (2002). According to their specification, individual (h) income in period (t) can be expressed as:

$$y_{h,t} = (1 + \gamma_y)^t \left[ (1 - \alpha_t) y_{h,0} + \alpha_t \bar{y}_0 \right]; \quad t = 0,...,T$$

(22)

where \( \gamma_y \) refers to the annual rate of (distribution-neutral\(^3\)) per-capita GDP growth, \( \alpha_t \) is period (t) percentage change in the Gini coefficient, while \( y_{h,0} \) and \( \bar{y}_0 \) refer to year 0 income of individual (h) and year 0 mean income, respectively.

Since our intention is to endogenize GDP growth as a function of the rate of accumulation of human capital, we will extend (22) in order to allow for a different per-capita GDP growth each period. Formally:

$$y_{h,t} = \prod_{s=0}^{t} (1 + \gamma_{y,s}) \left[ (1 - \alpha_t) y_{h,0} + \alpha_t \bar{y}_0 \right]; \quad t = 1,...,T$$

(23)

With the above formula, and for a given percentage change in the Gini coefficient and a poverty line (ycrit), it will be possible to compute poverty incidence as:

$$I_{t,t} = \left[ \sum_{h=1}^{\text{Pop}_t} I(y_{h,t} < \text{ycrit}) \right] / \text{Pop}_t$$

(24)

\(^3\) Regarding the role and nature of economic growth, the recent literature proposes several definitions related to the impact of growth on poverty. Less restrictive definitions suggest that we can talk about pro-poor growth as long as we observe an improvement in the poverty indicator under analysis, even if it implies a deterioration in income distribution (Kraay (2003)). More restrictive definitions, on the other hand, propose that growth can only be regarded as pro-poor if it provokes an improvement in income distribution (Kakwani and Pernia (1999)). The “type” of growth implied in equation (22) stands on an intermediate ground. In particular, it assumes that everyone’s income grows at the same rate so we can regard this “type” of growth as distribution-neutral.
where $\text{Pop}_t$ refers to the total population in period $(t)$. In this way, our model will be able to account for the potential impact that improvements in educational attainment have on the income generation capability of the population and the incidence of monetary poverty.

### 2.4 The Costing and Resource Constraint Block

We present the specific functional forms of cost functions for policy interventions related to the education sector. We also discuss the assumptions that will govern the behavior of the planner’s budget constraint.

In particular, micro-econometric results that stem from the education block imply the existence of five potential policy variables: the number of teachers in each educational cycle and the number of schools in primary and tertiary education. In accordance with the complementary nature of these variables, the total cost of intervention ($\text{TC}_i$) was estimated as follows.

Intervention implies choosing a final value (in year $T$) for the ratios of teachers and schools per student in each educational level ($\text{eduqual}_{i,t} ; i = 1, 2, 3$). In particular, and according to the results discussed in the education block, variable $\text{eduqual}$ refers to the product between the number of teachers and schools per student for primary and tertiary education, while it only refers to the number of teachers per student for the case of secondary education. Once the planner has chosen these three final values, we compute the annual growth rate of each $\text{eduqual}_{i,t}$ following: $\gamma_i = \left(\frac{\text{eduqual}_{i,T}}{\text{eduqual}_{i,0}}\right)^{1/T}$. The latter implies an annual growth factor for the number of teachers $\gamma_{\text{tea}}$ and schools $\gamma_{\text{sch}}$ in each educational level, which will depend on: (i) the endogenous evolution of the number of students enrolled in each educational level; and (ii) a fixed assumed ratio between the number of teachers and schools in each educational level$^4$.

---

$^4$ For the case of primary and tertiary education, the planner can provoke an increase in $\text{eduqual}$ by raising either the number of teachers or schools. In the absence of further restrictions, the planner will typically choose to raise $\text{eduqual}$ via the number of teachers since this is a less expensive input for the provision of educational
Given these endogenous growth rates, and unit costs for teachers and schools in each educational level, we can finally compute the total cost of intervention \( TC_i \) in education following:

\[
C_{Tea} = (Tea_i - Tea_{i,0}) \cdot UCTea = Tea_{i,0} \prod_{s=0}^{t} \gamma_{s(Tea),s} - 1 UCTea \\
C_{Sch} = (Sch_i - Sch_{i,0}) \cdot UCSch = Sch_{i,0} \prod_{s=0}^{t} \gamma_{s(Sch),s} (\gamma_{s(Sch),s} - 1) UCSch
\]

\[
TC_i = \sum_{i=1}^{3} C_{Tea,i,t} + \sum_{i=1}^{3} C_{Sch,i,t}
\]

where:
- \( C_{Tea,i,t} \) = Cost of additional teachers for educational level \( i \) in period \( t \)
- \( Tea_{i,t} \) = Number of teachers in educational level \( i \) in period \( t \)
- \( UCTea \) = Unit cost per teacher in educational level \( i \)
- \( C_{Sch,i,t} \) = Cost of additional schools for educational level \( i \) in period \( t \)
- \( Sch_{i,t} \) = Number of schools in educational level \( i \) in period \( t \)
- \( UCSch \) = Unit cost per school in educational level \( i \)

Finally, and regarding the planner’s budget constraint, we will impose the following condition:

\[
TC_i \leq \lambda Y_i \\
Y_i = Y_{i-1} (1 + \gamma_{i,t} + \gamma_{N})
\]

In fact, official projections\(^5\) contemplate a sustained reduction of the fiscal deficit (0.3% of GDP in year 2005) and the possibility of a surplus (of around 0.5% of GDP) by year 2009. Thus, our simulation exercise assumes fiscal equilibrium as the average situation for the period 2005-2015. In terms of the equations that govern our planner’s budget constraint (specified in the previous sections), this implies:

According to the current Fiscal Discipline Law $\lambda = 0.01$. Therefore, the above simply means that the planner has access to additional resources that amount to 1 percent of GDP each year to finance further intervention and comply with the fiscal rule.

3 Education, long-run growth and poverty

In this section we present our simulation results based on the model described above: one that accounts for the potential feedback between the education module and the macro block and links these results with the poverty block. In turn, enrolment and graduation rates will also depend on GDP growth via the effect of per-capita household expenditure as captured in the micro-econometric results discussed in the education block. Simulations were carried out considering that our planner seeks to achieve particular targets for selected education indicators and/or GDP growth itself, subject to the budget constraint explained in the previous section.

Thus, our simulation exercise will provide the necessary inputs to: (i) approximate the gains, in terms of increased GDP growth, that could stem from improvements in enrolment and graduation rates within the education sector; and (ii) discuss which type of educational services should be privileged if we seek improvements in enrolment rates per se, vs. improvements in poverty incidence indicators which, for a given percentage change in the Gini coefficient, have a one-to-one relationship with aggregate GDP growth.

Our analysis is based on the comparison of five different scenarios: (i) BaU – a no-intervention (business as usual) scenario, where no fiscal effort is devoted to increase the provision of educational services; (ii) MDG2 – an intervention scenario where our planner expands the provision of educational services in order to minimize loss defined as a function

$$D_i = (1 + r)D_{i-1} + G_i + TC_i - R_i$$
$$rD_{i-1} + G_i - R_i = 0$$
$$D_i - D_{i-1} \leq \lambda Y_i \Rightarrow TC_i \leq \lambda Y_i$$

---

6 Simulations were carried out using the General Algebraic Modeling System (GAMS).
of enrolment rates in primary education\(^7\); (iii) MDG2\(^*\) – an intervention scenario where our planner expands the provision of educational services in order to minimize loss as a function of both primary and secondary enrolment rates; (iv) MDG2\(^**\) – an intervention scenario where our planner expands the provision of educational services in order to minimize loss as a function of all enrolment rates\(^8\); and (v) MDG1 – an intervention scenario where our planner expands the provision of educational services in order to maximize GDP growth\(^9\). Thus, loss functions for the last four scenarios are given by\(^{10}\):

\[
\begin{align*}
LF_{\text{MDG2}} &= (1 - \text{entry}_T) \\
LF_{\text{MDG2}^*} &= (1 - \text{entry}_T) + (1 - \text{sec}_{\text{cont}}) \\
LF_{\text{MDG2}^{**}} &= (1 - \text{entry}_T) + (1 - \text{sec}_{\text{cont}}) + (1 - \text{sup}_{\text{cont}}) \\
LF_{\text{MDG1}} &= (10 - \gamma_{Y,T})
\end{align*}
\]

If we refer to the gains in terms of increased GDP growth, it is worth noticing that the model captures the effects of several driving forces. In particular, the main exogenous determinants of our results can be grouped in two: (i) those that affect the maximum attainable improvement in terms of GDP growth, which, according to equation (17) will basically depend on the productivity gains associated to individuals’ educational attainment \((\lambda_{Y_i}, \lambda_{Hi}; i = 1, 2, 3)\); and (ii) given (i), those that affect the proportion of this maximum attainable improvement that can be actually achieved under our BaU and intervention scenarios. Regarding the latter, the actual improvement under the BaU scenario will be mainly driven by the elasticity of enrolment and graduation rates with respect to per-capita expenditure. Given this, further improvements under the intervention scenarios will mainly depend on the elasticity of enrolment rates with respect to policy variables, the unit costs of intervention, the budget constraint, and the arguments included in our planner’s loss function.

---

\(^7\) Following the indicators originally targeted as part of the second MDG.

\(^8\) Scenarios (iii) and (iv) introduce an extension in the set of indicators related to the second MDG in order to account for educational attainment in the secondary and tertiary levels.

\(^9\) According to our poverty block, and for a given percentage change in the Gini coefficient (captured via parameter \(\alpha_i\)), poverty incidence will only depend on aggregate GDP growth. Therefore, in the context of our model, a planner concerned about maximizing GDP growth resembles a planner concerned about minimizing poverty incidence. This is why this scenario, where the loss depends on GDP growth itself, is referred as MDG1.

\(^{10}\) Targets for enrolment rates were fixed in 1 (100%). The target for aggregate GDP growth was fixed in 10%.
Figures 1 and 2 depict the evolution of the GDP growth rate and the moderate (or national) poverty headcount index, under each of the five scenarios considered\(^\text{11}\) (in Appendix 3 we present the evolution of each enrolment rate under these five scenarios). As revealed in Figure 1, the BaU scenario already predicts an increase of 0.82 percentage points in aggregate GDP growth if we compare year 0 (5.11%) and year 2015 (5.93%) values. As discussed above, this improvement depends on the elasticity of enrolment and graduation rates with respect to per-capita expenditure, which guarantees that enrolment and graduation rates do experience an improvement throughout the simulation period even if no specific additional policy interventions are in place.

\[\text{Figure 1: GDP growth (BaU and intervention scenarios)}\]

\(^{11}\) The GDP growth rate is obtained following equations (13) and (17). The poverty headcount index is obtained combining equations (23) and (24). Following historic trends regarding the evolution of the Gini coefficient, we assumed this index experienced an annual growth of 1.1% throughout the entire simulation period. This implied a value of \(\alpha_1 = 0.011\) for parameter \(\alpha_1\). In this way, we were able to move away from the distribution-neutral assumption implied in equation (22) and account for the effect of growth on poverty in a way more consistent with the recent Peruvian experience.
If we simulate our model under the first intervention scenario (MDG2) results reveal an increase of 1.20 percentage points in aggregate GDP growth if we compare year 0 and year 2015 values. This implies that, despite the fact that the enrolment rate in primary education reaches its target by year 2010\(^{12}\), there is only a marginal gain in terms of increased GDP growth with respect to the no intervention scenario.

Little further improvements are attained if we extend the set of arguments in the planner’s loss function to include enrollments in secondary education (MDG2*). Actually, the growth rate by year 2015 is as little as 0.12 percentage points above that obtained in the previous scenario.

Under the MDG2** and the MDG1 scenarios however, we do observe a significant increase with respect to the BaU scenario. In both cases, results reveal an increase of around 1.75

\(^{12}\) It must also be said that the probability of graduating within the primary cycle (grdprim) also reaches a value very close to 1 by year 2015. These results imply that the probability of entering grade 1 and finishing grade 6 at normative age is also close to 100%.
percentage points in aggregate GDP growth, which imply gains close to 0.95 percentage points with respect to the no intervention scenario by year 2015. At this point it is worth highlighting that almost no difference can be observed if we compare GDP growth rates under the MDG1 and MDG2** scenarios. This means that, given the restrictions imposed in our model, the gains in terms of increased aggregate growth do not depend on whether our planner is concerned about all enrolment rates per se, or concerned about growth (or poverty) itself. These restrictions are basically: (i) the elasticity of enrolment rates in tertiary education with respect to policy variables related to this educational cycle; (ii) the unit costs of intervention\textsuperscript{13}; and (iii) the budget constraint\textsuperscript{14}.

Obviously, a similar situation is observed if we analyze the behavior of the poverty headcount index. In particular, and as revealed in Figure 2, the marginal expansion in aggregate GDP growth gained via intervention under the MDG2 and MDG2* scenarios exhibit almost no effect in terms of poverty reduction with respect to the BaU scenario. A different situation is observed under the MDG1 and MDG2** scenarios, where the additional expansion in aggregate GDP growth gained via intervention provokes a further 1.7% permanent decline in poverty by year 2015: under the BaU scenario poverty incidence falls from 48% to 32.2%; under these intervention scenarios poverty falls to a figure close to 30.5%. Once again, these results are independent of our planner’s preferences: given the available policy instruments (human resources and infrastructure in every educational level), their unit costs and the budget constraint, it would be almost equivalent in terms of its final effect on poverty to ask our planner to close the existing gaps in all enrolment rates or to ask her to minimize poverty.

If we believe education indicators are among those targeted as MDGs because the accumulation of human capital is closely related to households’ long run income generation potential, then we should also believe that targeting education indicators is important to the extent in which they serve as proxies of future poverty. Our claim is that MDGs can serve as

\textsuperscript{13} According to imputed unit costs (provided by the Ministry of Education), teachers in tertiary education cost twice as much as those in primary or secondary education. Infrastructure (schools), on the other hand, costs three times as much.

\textsuperscript{14} The budget constraint is binding under the MDG2*, MDG2**, and MDG1 scenarios. When focused only on primary education (MDG2), resources devoted to intervention amount, on average, to 0.24% of GDP each year.
a basic template for the design and evaluation of social policy intervention because, together with the standard poverty measures, they also involve targets for a broader set of variables that, if attended, should grant intervention the ability of transferring the necessary assets to create more egalitarian opportunities of income generation in the future. In fact, and as argued in Yamada and Castro (2007) it should not be difficult to expand social assistance (such as cash or food transfers) while the economy is booming and observe a short run decline in poverty headcount indexes as a result of their combined effects. However, this improvement will only be temporary if social programs have failed to deliver those assets that guarantee that households can attain and secure a larger income generation potential\(^{15}\).

We believe the results presented here lie at the core of this discussion. For policy intervention to be effectively transferring households the ability of securing a larger income generation potential, it should (in terms of our model and when compared to a BaU scenario) maximize the gain in terms of increased long run GDP growth and further permanent reduction in poverty incidence. Following the results discussed above, our simulation exercise has revealed that if we are to target education indicators so as to maximize this gain (given constraints), we need to extend the original set of MDGs in order to foster access to higher educational levels besides primary. In fact, asking our planner to minimize poverty (or maximize growth) using the set of policy variables considered in the model implies engineering intervention in the educational sector so as to transfer households the necessary assets to attain a larger income generation potential in the long run. Which enrolment rates should be considered, *per se*, in order to mimic this situation? Results discussed above show that, given restrictions, we also need to target enrolment rates in secondary and tertiary education.

### 4 Conclusions

The model developed has provided the necessary inputs to: (i) estimate the gains, in terms of potential increased GDP growth an poverty reduction, that could stem from intervention

\(^{15}\) As accounted for in Yamada and Castro (2007), the economic recovery experienced between 1991 and 1997 was accompanied by a significant reduction in poverty incidence from 54.2% to 46.4%, while the moderate recession period experienced between 1998 and 2001 wiped away these achievements and poverty was again as high as 54.5% by the end of year 2001.
leading to improvements in enrolment and graduation rates within the education sector; and (ii) discuss which type of educational services are to be considered if we seek improvements in enrolment rates per se, vs. improvements in households’ income generation potential, being the latter a critical element to be taken into account when designing intervention in the educational sector.

Regarding the first of these two objectives, our simulations reveal that with additional funds which amount, on average, to 1% of GDP each year, expansions in the provision of educational services in all three levels could add, by year 2015, an extra 0.95 and 1.70 percentage points in terms of long-run GDP growth and permanent reduction in poverty incidence, respectively.

Regarding the second objective, our simulations reveal that in order to engineer intervention in the educational sector so as to transfer households the necessary assets to attain a larger income generation potential in the long run, we need to extend the original set of MDG indicators to account for access to higher educational levels besides primary. In fact, the gains (in terms of added GDP growth and poverty reduction) are only marginal if we limit ourselves to the provision of education services related to the primary cycle. On the other hand, if the planner is concerned about enrolment rates in all three cycles, final results in terms of long-run growth and poverty reduction mimic a situation where our planner is concerned about maximizing growth (or minimizing poverty).

As discussed in other recent research efforts (Beltrán et al, 2004; Castro and Yamada, 2006), and confirmed in this one, a seven percent sustained GDP growth rate proves to be an important pre-condition to cut national poverty by half by year 2015. This paper suggests an answer to the question of whether the MDG framework could provide, by itself, an engine to foster such a growth rate. The answer is yes: education, and this assessment has revealed that, in the Peruvian case, it should be understood as education in all three levels.
References


Bourguignon, F., F. Ferreira and N. Lustig (eds.) (2005), The microeconomics of income distribution dynamics (in East Asia and Latin America), The World Bank and Oxford University Press.


ECLAC-IPEA-UNDP (2002), “Meeting the Millennium Poverty Reduction Targets in Latin America and the Caribbean”.


Appendix 1: Econometric estimations for the Macro block

1. Estimating the stock of human capital when returns matter

Typically, the stock of human capital is computed considering the number of individuals corrected by the number of completed years of schooling. In this way, a person with completed primary will contribute to the stock of human capital six times as much as a person with no education (see, for example, Barro and Lee (2000)).

For the purpose of our analysis, and following equation (14) in the main text, we will instead consider the returns (in terms of increased earnings in the labor market) associated to each educational level. In particular, and according to the ENAHO 2004 household survey, individuals with each of the educational levels considered exhibit the proportionate earnings (with respect to no education) reported in Table 1 below. These correspond to the values of \( \lambda_{Y_i} \) and \( \lambda_{H_i} \) used to estimate the stock of human capital, and resemble the results discussed in Yamada (2006) where, by means of an extended Mincerian earnings equation, they proved that returns to education exhibit a convex behavior with respect to the educational level (see Graph 1).

<table>
<thead>
<tr>
<th>Educational level</th>
<th>Productivity (( \lambda ))</th>
</tr>
</thead>
<tbody>
<tr>
<td>No education</td>
<td>( \lambda_{Y1} ), ( \lambda_{H1} )</td>
</tr>
<tr>
<td>Less than completed primary</td>
<td>( \lambda_{Y1} )</td>
</tr>
<tr>
<td>Completed primary</td>
<td>( \lambda_{Y2} )</td>
</tr>
<tr>
<td>Less than completed secondary</td>
<td>( \lambda_{Y2} )</td>
</tr>
<tr>
<td>Completed secondary</td>
<td>( \lambda_{Y3} )</td>
</tr>
<tr>
<td>Less than completed tertiary</td>
<td>( \lambda_{Y3} )</td>
</tr>
<tr>
<td>Completed tertiary</td>
<td>( \lambda_{Y3} )</td>
</tr>
</tbody>
</table>

Table 1: Productivity associated to each educational level
2. Growth accounting exercise

In order to provide an estimate for the rate of growth of technology ($\gamma$) (required to estimate long-run GDP growth following equation (13) in the main text), we relied on an empirical version of (1). Formally:

$$\gamma_{Y,t} = \beta \gamma_{K,t} + (1 - \beta) \gamma_{HY,t} + \epsilon_i$$

where the residual ($\epsilon_i$) accounts for the rate of growth of technology. Data for aggregate GDP and the stock of physical capital were obtained from the statistical series provided by the Peruvian Central Bank for the period 1960-2000. A time series for the stock of human capital devoted to production, on the other hand, was built using the estimates of the number of people in the labor force with each educational level provided in Carranza et al. (2003), and our own estimates of the productivity of each type of human capital ($\lambda_{y_i}$) as described above. Finally, growth rates for each of these variables were computed using the trend component of each series estimated via a Hodrick-Prescott filter.
The table below presents our results for the estimation of parameter $\beta$ and the historical value of $\gamma_A$ used in the simulation exercise.

**Table 2: Results of the growth accounting exercise**

### Estimation of parameter beta

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_{K,t}$</td>
<td>0.41</td>
<td>0.00</td>
</tr>
<tr>
<td>$\gamma_{HY,t}$</td>
<td>0.59</td>
<td>0.00</td>
</tr>
</tbody>
</table>

### Imputed growth rates for the simulation exercise

<table>
<thead>
<tr>
<th>Variable</th>
<th>Growth rate</th>
</tr>
</thead>
<tbody>
<tr>
<td>Residual (A)</td>
<td>1.2%</td>
</tr>
</tbody>
</table>
Appendix 2: Econometric estimations for the education block: Enrolment and graduation rates

Table 1: Probability of enrolling in primary education at normative age (g1entry)

Sample: population (6 year-olds) not enrolled in year 2002; y = 1 if enrolled in primary in year 2003.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>P-value</th>
<th>Year 0 Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Per-capita household expenditure</td>
<td>0.0014735</td>
<td>0.000</td>
<td>0.2211</td>
</tr>
<tr>
<td>Teachers per student in primary education times number of schools per student in primary education (provincial level)</td>
<td>1726.944</td>
<td>0.068</td>
<td>0.0661</td>
</tr>
<tr>
<td>Access to adequate water services (1 if access; 0 otherwise)</td>
<td>1.266016</td>
<td>0.009</td>
<td>0.0431</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.084624</td>
<td>0.039</td>
<td></td>
</tr>
</tbody>
</table>

Table 2: Probability of enrolling in secondary education at normative age (grdcontsec)

Sample: 12 year-olds that were enrolled in primary and graduated in year 2002; y = 1 if enrolled in secondary in year 2003.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Coefficient</th>
<th>P-value</th>
<th>Year 0 Elasticity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Teachers per student in secondary education (provincial level)</td>
<td>10.52603</td>
<td>0.300</td>
<td>0.1399</td>
</tr>
<tr>
<td>Place of residence (1 if urban; 0 otherwise)</td>
<td>0.8503937</td>
<td>0.0020</td>
<td>0.1369</td>
</tr>
<tr>
<td>Household head educational attainment (1 if at least completed primary; 0 otherwise)</td>
<td>0.6902159</td>
<td>0.0300</td>
<td>0.1216</td>
</tr>
<tr>
<td>Constant</td>
<td>-0.5673254</td>
<td>0.443</td>
<td></td>
</tr>
</tbody>
</table>

Due to the functional form relating determinants to enrolment rates in all models, any change in the level of a determinant will imply a change in all elasticities comprised in the same model. In fact, and as explained in the main text, all determinants exhibit decreasing marginal returns.
### Table 3: Probability of enrolling in tertiary education at normative age (grdcontsup)

Sample: 17 year-olds that were enrolled in secondary and graduated in year 2002; \( y = 1 \) if enrolled in tertiary in year 2003.

<table>
<thead>
<tr>
<th>Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Per-capita household expenditure</td>
</tr>
<tr>
<td>Teachers per student in tertiary education times number of schools per student in tertiary education (regional level)</td>
</tr>
<tr>
<td>Gender (1 if female; 0 otherwise)</td>
</tr>
<tr>
<td>Household head educational attainment (1 if tertiary; 0 otherwise)</td>
</tr>
<tr>
<td>Constant</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Variable</th>
</tr>
</thead>
<tbody>
<tr>
<td>Child mortality incidence (regional level)</td>
</tr>
<tr>
<td>Wage gap: completed primary vs. no education (regional level)</td>
</tr>
<tr>
<td>Per-capita household expenditure</td>
</tr>
<tr>
<td>Teachers per student in primary education times number of schools per student in primary education (provincial level)</td>
</tr>
<tr>
<td>Access to adequate water services (1 if access; 0 otherwise)</td>
</tr>
<tr>
<td>Access to adequate sanitation services (1 if access; 0 otherwise)</td>
</tr>
<tr>
<td>Constant</td>
</tr>
</tbody>
</table>

### Table 4: Probability of graduating within primary or secondary education (grd)

Sample: children between 6 and 16 years of age that in year 2002 were enrolled in some grade in primary or secondary; \( y = 1 \) if approved grade.
Appendix 3: Enrolment rates under the five scenarios

Primary education (g1entry)

Secondary education (grdcontsec)