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Human Capital and Equity-Adjusted Income: A BMA-Based Decomposition Approach

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ABSTRACT

This paper utilizes the Bayesian Model Averaging (BMA) methodological approach to explore how human capital affects equity-adjusted income and its growth rate, commonly described as inclusive growth and defined as income growth adjusted for changes in income distribution. The equity-adjusted income measure that we use is broken down into real GDP per capita and the income equity index (IEI) as its component parts. Framed in this way, the measure is designed to capture how fairly different levels and changes in national income are shaped. In this paper, we study how the preferred measure responds to human capital, a factor widely established as a major driver of both higher income growth and greater equity. We proxy human capital using variables for education and health and, alongside a set of standard growth determinants as controls, incorporate them into a BMA estimation setting. In this context, the main objective of the paper is to determine whether human capital contributes to equity-adjusted income mainly by increasing real GDP per capita or by improving income distribution. Put differently, the paper asks which of these two dimensions accounts more for the overall link between human capital and equity-adjusted income. The estimation results indicate that human capital variables do not exhibit robust effects on inclusive growth rates as originally defined. However, both education and health show robust and positive effects on the level of equity-adjusted income in logarithmic form. The structural decomposition we perform further suggests that the GDP per capita channel is materially more important, although education also retains a meaningful role through the income equity component. This outcome holds regardless of which proxy is included in the estimation.

Keywords: *inclusive growth, GDP growth, human capital, income inequality*

JEL Classification: I3, O1, O4

INTRODUCTION

In their influential paper, Anand, Mishra, and Peiris (2013) defined inclusive growth as a composite variable comprising two components: the growth of real gross domestic product (GDP) per capita and the growth of a specially derived income equity index (IEI). In this framework, inclusive growth may also be viewed as the growth rate of equity-adjusted income, while equity-adjusted income itself represents the underlying level variable that combines income growth and income distribution. Using a stochastic panel model specification with both country and period effects, Anand et al. (2013) explored the influence of a variety of variables on inclusive growth. Education, measured as mean years of schooling, was one of the variables included in the model. This is particularly noteworthy, since this variable represents one of the main proxies for human

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capital and has been consistently shown to significantly affect the economic growth rate in panel studies (Lucas, 1988; Mankiw et al., 1992; Barro & Lee, 1994; Benhabib & Spiegel, 1994). Education has also been identified as one of the main drivers of the income inequality component of inclusive growth, typically measured by an income inequality index (De Gregorio & Lee, 2002; Goldin & Katz, 2008; Lustig et al., 2013). Education and health, as key proxies for human capital, have also been found to be statistically significant determinants of inclusive growth in other studies (Raheem et al., 2018).

There are also important theoretical arguments suggesting that human capital may strongly affect not only the overall level of economic development, as proposed in neoclassical (Mankiw et al., 1992) and endogenous growth theories (Lucas, 1988; Romer, 1990), but also the degree of its inclusiveness. In this context, particularly relevant is the discussion of compression effects, whereby the education premium declines as the share of individuals with higher levels of human capital increases (Knight & Sabot, 1983).

Even though the potential effect of human capital on inclusive growth may operate through both components, none of the earlier studies has explicitly examined how this effect is transmitted to inclusive growth. More specifically, the existing literature has not established whether human capital contributes more to equity-adjusted income through higher real GDP per capita or through improvements in income distribution, nor has it clarified whether such effects are more clearly detectable in the level of equity-adjusted income than in inclusive growth rates themselves. This gap is important because identifying the dominant pathway can help clarify how human capital shapes inclusive development.

Against this background, this paper addresses two main research questions. First, does human capital exert a statistically meaningful effect on inclusive growth, on equity-adjusted income as its underlying level variable, and on their underlying components? Second, if such an effect exists, is it transmitted primarily through the real GDP per capita component or through the income equity component? Accordingly, the main objective of the study is to determine which of these two channels accounts more for the overall link between human capital and equity-adjusted income, while also assessing whether human capital exerts robust effects on inclusive growth rates as originally defined.

To address this issue, we adopt the following strategy in this paper. Considering a sample of countries between 2009 and 2021, we take both education, measured by mean years of schooling, and health, proxied by life expectancy at birth, as the human capital variables of interest. As a set of possible controls, we restrict ourselves to the variables identified by Mirestean and Tsangarides (2009) as robust determinants of economic growth. To obtain robust estimates of the effect of human capital on inclusive growth, on equity-adjusted income, and on their components, we employ the Bayesian Model Averaging (BMA) approach. This approach helps address the issue of model uncertainty, which may affect many of the inclusive growth studies conducted so far. In this way, it may significantly reduce the risk of making statistical inferences based on inadequately specified model formulations (Hoeting et al., 1999).

The expected contribution of this paper is threefold. First, it adds to the literature on inclusive growth by moving beyond the identification of determinants and explicitly examining the pathway through which human capital affects equity-adjusted income and, more broadly, inclusive growth. Second, it contributes methodologically by applying the BMA framework to this question, thereby addressing model uncertainty in a more systematic manner. Third, by decomposing the overall effect of human capital into GDP per capita and income-equity components, the paper provides evidence on the relative importance of these two channels. In doing so, it offers a clearer understanding of whether human capital matters primarily as a driver of economic expansion, as a driver of distributional improvement, or both. This contribution is especially relevant in light of the paper's findings, which suggest that the GDP per capita channel is materially more important and that the more robust results relate to equity-adjusted income rather than to inclusive growth rates themselves.

The remainder of the paper is structured as follows. Section 1 reviews the relevant literature. Section 2 presents the sample, the variables, and the data sources used in the empirical analysis. Section 3 outlines the methodological framework. Section 4 reports the estimation results and the structural decomposition findings. The final section concludes.

LITERATURE REVIEW

Inclusive growth has been conceptually discussed in a number of studies (Ianchovichina & Lundström, 2009; Klasen, 2010; McKinley, 2010). These studies cover multidimensional aspects that are thought to be associated with inclusive growth. However, the most concrete steps toward the development of a clear and measurable concept were taken by Anand, Mishra, and Peiris (2013). These authors defined inclusive growth as a composite index constructed as the sum of two components, in the following manner (Anand et al., 2013):

$$\frac{d\bar{y}^*}{\bar{y}^*} = \frac{d\bar{y}}{\bar{y}} + \frac{d\omega}{\omega} \tag{1}$$

Equation (1) identifies the inclusive growth rate, $(\frac{d\bar{y}^*}{\bar{y}^*})$, as the sum of the real GDP per capita growth rate, $(\frac{d\bar{y}}{\bar{y}})$, and the growth rate of the income equity index (IEI). Anand and colleagues (2013) define IEI as the ratio between what they call "the social mobility index" $(\bar{y}^*)$ and real GDP per capita $(\bar{y})$:

$$\omega = \frac{\bar{y}^*}{\bar{y}} \tag{2}$$

Constructed in this way, the IEI can be viewed as a measure of the deviation of the actual income distribution from one in which everyone has the same income. To obtain a measure of the IEI, however, the values of the social mobility index, or what we refer to as equity-adjusted income, are required. Anand and colleagues (2013) calculate this index by integrating the average income of the bottom *i* percent of the population across percentiles $(\bar{y}_i)$:

$$\bar{y}^* = \int_0^{100} \bar{y}_i di \tag{3}$$

Anand et al. (2013) used this measure to estimate how different variables affect inclusive growth. They employed a heavily unbalanced panel dataset covering 143 countries over the period from 1980 to 2010. Anand and colleagues (2013) also chose a stochastic model specification with both country and period effects. Their estimation results indicate that several variables have a statistically significant effect on inclusive growth across different model specifications. Among the variables showing the most consistent effects were lagged GDP per capita and inflation, both of which had negative effects, and trade openness and education, both of which had positive effects on the rate of inclusive growth.

Subsequent studies have produced similarly important findings. A number of different variables have thus been identified as significant determinants of inclusive growth. These include fiscal redistribution (Aoyagi & Ganelli, 2015), higher productivity growth (Alekhina & Ganelli, 2023), lower unemployment rates (Aoyagi & Ganelli, 2015), institutional quality (Aslam et al., 2021), ease of doing business (Asongu & Odhiambo, 2019), social, financial, and digital inclusion (Aslam et al., 2021; Cui et al., 2022), public spending (Angulo-Bustinza et al., 2023), and the savings rate (Alekhina & Ganelli, 2023), among other variables. It is worth noting that some of these studies explicitly used the measure developed by Anand and colleagues (Anand et al., 2013; Alekhina & Ganelli, 2023; Aoyagi & Ganelli, 2015; Aslam et al., 2021), while others relied on less complex proxies (Angulo-Bustinza et al., 2023; Asongu & Odhiambo, 2019; Cui et al., 2022; Raheem et al., 2018).

Yet, considering this body of literature as a whole, variables commonly viewed as components of human capital have repeatedly been shown to exert a positive influence on inclusive growth. Starting from the finding of Anand et al. (2013), who estimated the coefficient on education to range between 0.12 and 0.78, multiple other studies have reached similar conclusions. Raheem et al. (2018), for instance, found that public expenditure on both education and health may have a positive impact on inclusive growth. The coefficient on the former was estimated at around 0.08, while the coefficient on the latter was estimated at around 0.11. Tella and Alimi (2016) supported these claims with respect to health expenditure.

These findings are not surprising, given that human capital variables have been identified by many researchers as important drivers of both components of inclusive growth. As for the first of these components, the real GDP per capita growth rate, its relationship with the development of human capital has been emphasized by some of the most influential scholars in the economic growth literature. On a theoretical level, particularly notable is the work of Robert Lucas (1988), who advanced an endogenous growth framework that assigns a central role to human capital accumulation. According to Lucas (1988), human capital can primarily be accumulated in two ways: through schooling and through learning by doing. These two mechanisms play a complementary role in enabling human capital to enhance GDP per capita growth.

Notably, the importance of human capital as a driver of economic growth, proxied by education variables, has been empirically confirmed by studies such as Mankiw et al. (1992), Hanushek and Kimko (2000), Bassanini and Scarpetta (2002), and Hanushek and Woessmann (2012), among many others.[1] Health variables, such as life expectancy at birth, which are also viewed as important proxies for human capital, have similarly been identified as drivers of growth in empirical studies (Barro, 2013; Bloom et al., 2004). Human capital variables have also been investigated within the context of the BMA approach, albeit with mixed results in terms of robustness (Dima & Dima, 2018; Mirestean & Tsangarides, 2009; Moral-Benito, 2012).

With regard to income distribution, Knight and Sabot (1983) discussed what they termed the composition and compression effects. As the share of educated individuals in the total population increases, the composition effect is hypothesized to initially raise income inequality, but eventually to reduce it once that share becomes sufficiently large. Knight and Sabot (1983) placed particular emphasis on the compression effect, under which inequality declines as the education premium falls with an increase in the number of educated individuals. Moreover, numerous empirical studies have identified a significant effect of human capital on income inequality. As expected, this effect has been found to be predominantly negative. The variables used to capture the effect of human capital have been based even more heavily on education. These measures include indicators primarily related to education quality (Blau & Kahn, 2005; Checchi & van der Werfhorst, 2014) as well as average years of schooling (Barro, 2000; De Gregorio & Lee, 2002).

In light of these findings, it is not unreasonable to expect human capital to have a significant effect on equity-adjusted income, likely through both of its components. However, although human capital has been consistently identified as a major determinant of both components separately, no study on inclusive growth has explicitly examined the relative contribution of each component channel to the overall effect of human capital on inclusive growth. The primary aim of this study is to fill this research gap. Accordingly, the following sections explore which of these two channels primarily transmits the effect of human capital on inclusive growth and equity-adjusted income, if such an effect exists at all.

[1] It is important to note that some studies fail to find a positive relationship between education-based human capital and economic growth (Bils & Klenow, 2000; Nedić et al., 2020; Szécsi & Szunomár, 2024).

DATA AND METHODOLOGY

Like previous studies that cover the empirical determinants of inclusive growth, our research is based on panel data. Our sample is primarily determined by the availability of data on income percentile distributions. By browsing the World Bank Poverty and Inequality Platform (World Bank, 2025a), one of the main sources of income distribution data, we identified 50 countries with relatively extensive coverage of income percentile distributions over time. This set of countries constitutes our basic sample. Given the established data-collection rules, these countries are mostly concentrated in Europe and the Americas. The first column of Table 1 lists these countries in alphabetical order.

Table 1. Countries in the sample

Countries in the basic sample (income-based distribution measure)	Countries added in the upgraded sample (consumption-based distribution sample)
Austria, Belgium, Bolivia, Brazil, Bulgaria, Canada, Colombia, Costa Rica, Croatia, Cyprus, Czechia, Denmark, Dominican Republic, Ecuador, El Salvador, Estonia, Finland, France, Germany, Greece, Honduras, Hungary, Iceland, Ireland, Israel, Italy, Korea Republic, Latvia, Lithuania, Luxembourg, Malta, Montenegro, Netherlands, North Macedonia, Norway, Panama, Paraguay, Peru, Poland, Portugal, Romania, Serbia, Slovenia, Slovak Republic, Spain, Sweden, Switzerland, United Kingdom, United States, Uruguay	Albania, Armenia, Belarus, China, Georgia, Indonesia, Iran, Kazakhstan, Kyrgyz Republic, Moldova, Russian Federation, Thailand, Turkey, Ukraine

Source: World Bank (2025a).

When it comes to the time dimension of our sample, we focus on the period from 2009 to 2021. We chose this time range in order to obtain the largest possible sample, given the availability of data across countries. The same time frame applies to the countries listed in the second column of Table 1, which we add in order to create our upgraded sample. Due to the established data-collection rules, these countries only have distribution data based on consumption.

Augmenting our sample with a consumption-based inclusive growth measure benefits us in two ways. First, it increases the number of possible observations in our sample from 650 to 832, which is not insignificant. Second, it helps us assess whether our estimated parameter values remain stable under different measurement rules. Data on income and consumption distributions provide the inputs that we include in equation (3) to obtain the relevant equity-adjusted income data for each country in a given year. The corresponding integration is carried out using Simpson's rule. Inclusive growth rates are then obtained by first-differencing the relevant log values of equity-adjusted income. Because inclusive growth in this framework is defined as the growth rate of equity-adjusted income, the latter remains the underlying level variable of conceptual interest throughout the analysis. For this reason, in addition to estimating models for inclusive growth rates, we also consider whether the explanatory variables display a clearer relationship with the level of equity-adjusted income itself. This allows us to distinguish between effects on the rate of change of equity-adjusted income and effects on its level.

The above discussion leaves us with the question of which variables should be chosen as independent variables, either as human capital proxies or as control variables. Given the limited scope of this paper, our choice of independent variables is guided by the results of the study by Mirestean and Tsangarides (2009). This study provides a valid benchmark, as it identifies robust growth determinants. These results are based on the implementation of the Limited Information Bayesian Model Averaging (LIBMA) approach, which is characterized by the inclusion of moment conditions in a more general Bayesian framework to account for a variety of issues, including dynamics and endogeneity. The variables identified as robust in that study, and which we therefore include in our analysis, are listed in Table 2.

Table 2. Independent variables

Human capital proxy variables	Control variables
Log(years of schooling) Life expectancy at birth (total)	Log(initial equity-adjusted income) Log[fixed capital formation (% of GDP)] Log(population growth) Log(inflation) Central government debt (% of GDP) Trade openness (% of GDP)

Source: Mirestean and Tsangarides (2009).

As can be seen, one of the variables identified as robust by Mirestean and Tsangarides (2009) is life expectancy at birth (total), which serves as our proxy for the health dimension of human capital. Another human capital proxy used by Mirestean and Tsangarides (2009) is mean years of schooling. Although it was not identified as robust by these authors, it is included in our study as the proxy for the education dimension of human capital. The other variables listed as robust growth determinants in Table 2 are incorporated as control variables. These include fixed capital formation (as a percentage of GDP), population growth, inflation, central government debt, and trade openness (Mirestean & Tsangarides, 2009). To account for the fact that our study deals with inclusive growth rather than standard GDP per capita growth, we include initial equity-adjusted income instead of initial GDP per capita that was identified as a robust growth determinant by Mirestean and Tsangarides (2009). This substitution is intended to preserve the logic of standard convergence specifications while adapting it to the Anand et al. (2013) framework: just as initial GDP per capita is used when the dependent variable is GDP per capita growth, initial equity-adjusted income is more appropriate when the dependent variable is inclusive growth, understood as the growth rate of equity-adjusted income. In other words, equity-adjusted income is the underlying level variable whose growth is being explained in our framework, and its initial value therefore plays the same conceptual role that initial GDP per capita plays in conventional growth regressions. This choice also ensures consistency between the definition of the dependent variable and the initial-condition variable used in the model, as relying on initial GDP per capita alone would capture only one dimension of the broader concept embodied in inclusive growth. We also follow Mirestean and Tsangarides (2009) in deciding which independent variables to transform into logarithmic form.

Unlike equity-adjusted income and its growth rate, data for each of our independent variables are readily and fully available from established data sources. The main source is the well-known World Development Indicators database (World Bank, 2025b), from which most of the data are drawn. The main exception is central government debt, for which the data are drawn from the International Monetary Fund's Global Debt Database (IMF, 2025a) and World Economic Outlook (IMF, 2025b). Data on mean years of schooling are taken from the United Nations Development Programme's Human Development Reports data center (United Nations Development Programme, n.d.).

Our goal in this paper is to make our coefficient estimates as robust as possible in light of model uncertainty. To do so, we employ the Bayesian Model Averaging (BMA) methodology. This approach considers a variety of models that may adequately capture the relationship between the dependent variable and the variables that affect it, thus addressing the issue of whether any particular specification chosen by researchers is in fact adequate (Hoeting et al., 1999; Koop, 2003).

The BMA approach is not based on simple averaging. Its building blocks are grounded in the Bayesian framework. This means that the starting point of any estimation is the choice of relevant priors. Since the approach is extended to explore different models, the prior choices include not only those for the coefficients of interest, but also those for the model space itself. In this paper, we opt for the following priors for the model and coefficient space, respectively:

1. **Uniform prior for model selection.** This prior assumes an equal probability for each possible model specification. Even though some proposals suggest penalizing specifications with a larger set of variables, our decision to limit the model space to a relatively small set of variables whose robustness has been established earlier prevents us from considering models with a very large number of regressors.
2. **Zellner's g-prior for coefficient estimation.** Besides mirroring decisions made in the earlier literature (Fernández et al., 2001; Ley & Steel, 2009; Moral-Benito, 2012), this prior choice allows us to vary and control several properties of the coefficients, including the level of prior informativeness.

These prior choices are the first step toward obtaining the estimates that we wish to report. Since we average across models, the situation is somewhat more complex. Having only eight potential regressors makes it much easier to resort to exhaustive enumeration instead of using sampling procedures such as the commonly used MC^3 algorithm.[2] Yet, there are other complex steps that need to be taken. One of the main ones is the calculation of the posterior inclusion probability (PIP_k) for each potential regressor in the model. The way to obtain it can be summarized by the following equation:

$$PIP_k = \sum_{j=1}^{J} \omega_j I_k(M_j) \tag{4}$$

Clearly, PIP_k represents a sum of posterior model probabilities (ω_j) weighted by the inclusion indicators $I_k(M_j)$ that are dummy variables taking the value 1 if the variable whose posterior inclusion probability is being considered is included in the given model. To obtain the relevant posterior model probabilities, we need to use the aforementioned model-selection prior and to calculate the relevant marginal model likelihoods. The calculation of the former requires us to obtain the within-model posterior coefficient distribution. This is achieved by applying Bayes' formula, which combines the coefficient priors with the corresponding marginal likelihoods of the coefficients. The final and crucial step involves calculating the model-averaged posterior mean and posterior standard deviation estimates using the following equations:

$$\bar{\beta}_k = \sum_{j=1}^{J} \omega_j \, \mu_{k|j} \tag{5}$$

$$\sqrt{V[\beta_k \mid \mathrm{y}]} = \sqrt{\sum_j \omega_j v_{k|j} + \sum_j \omega_j (\mu_{k|j} - \bar{\beta}_k)^2} \tag{6}$$

Equation (5) shows that the BMA posterior coefficient mean estimate ($\bar{\beta}_k$) equals the within-model posterior coefficient means averaged by the posterior model probabilities. Equation (6), on the other hand, identifies the BMA posterior coefficient standard deviation (which is the square root of the total variance) with the square root of the sum of the averaged within-model ($\sum_j \omega_j v_{k|j}$) and between-model variances ($\sum_j \omega_j (\mu_{k|j} - \bar{\beta}_k)^2$).

Our work in this paper does not end with the calculation of the BMA posterior coefficient mean and standard deviation estimates. The final step is the exploration of the two channels through

[2] More on this type of algorithm and its specific application to BMA can be found in Madigan & York (1995).

which human capital affects inclusive growth and equity-adjusted income. To do so, we first obtain the BMA posterior coefficient mean estimates of the effect of human capital on each of the two components of inclusive growth and equity-adjusted income, using the same set of independent variables listed in Table 2. We then proceed by applying the following type of structural channel decomposition, inspired by the growth-accounting approach (Barro & Sala-i-Martin, 2003):

$$\alpha = \frac{\bar{\beta}_{gdppcg}}{\bar{\beta}_{ig}}; \quad 1 - \alpha = \frac{\bar{\beta}_{ieig}}{\bar{\beta}_{ig}} \tag{7}$$

Clearly, $\bar{\beta}_{gdppcg}$, $\bar{\beta}_{ieig}$ and $\bar{\beta}_{ig}$ stand for the BMA posterior coefficient mean estimates of the effects of human capital on GDP per capita growth, income equity index growth, and their sum, respectively. The parameters α and $1-\alpha$, on the other hand, refer to the relative importance weights of the effect of human capital on two inclusive growth components. Even though they are not directly observable, these parameters are somewhat analogous to factor income shares in the growth-accounting approach. Their role is to reveal how the relevant channels transmit the effect of human capital to inclusive growth.

RESULTS AND DISCUSSION

Consider now what emerges when we apply the above methodology to our data. Before proceeding with the BMA estimation, we compute Pearson correlation coefficients for the variables included in our modeling procedure. The results of the correlation analysis for both the basic and the upgraded samples are reported in Table 3.

Table 3. Pearson correlation analysis for both samples

Variables	Inclu-sive growth	Log(initi al soc mob index)	Log(fixe d cap form)	Log (yrs of schooling)	Life expecta ncy at birth	Log (pop growth)	Log (infla tion)	Central governm ent debt	Trade open-ness
Basic sample									
Inclusive growth	1								
Log(initi soc mob index)	-0.17	1							
Log(fixed cap form)	0.14	0.06	1						
Log(yrs of schooling)	-0.06	**0.79**	0.19	1					
Life expectancy at birth	-0.19	**0.83**	-0.01	0.53	1				
Log(pop growth)	-0.09	-0.02	0.11	-0.18	0.21	1			
Log(inflation)	0.08	-0.36	0.04	-0.33	-0.36	0.07			
Central government debt	-0.13	0.20	-0.52	-0.003	0.32	-0.09	-0.21	1	
Trade openness	0.10	0.37	0.13	0.33	0.16	0.01	-0.19	-0.16	1

Variables	**Inclu-sive growth**	**Log(initial soc mob index)**	**Log(fixed cap form)**	**Log (yrs of schooling)**	**Life expectancy at birth**	**Log (pop growth)**	**Log (inflation)**	**Central government debt**	**Trade open-ness**
Upgraded sample									
Inclusive growth	1								
Log(initial soc mob index)	-0.16	1							
Log(fixed cap form)	0.13	-0.11	1						
Log(yrs of schooling)	-0.07	**0.72**	0.04	1					
Life expectancy at birth	-0.175	**0.79**	-0.20	0.43	1				
Log(population growth)	-0.10	-0.05	0.18	-0.20	0.15	1			
Log(inflation)	0.03	-0.35	0.23	-0.22	0.45	0.07	1		
Central government debt	-0.14	0.24	-0.50	0.03	0.39	-0.09	-0.26	1	
Trade openness	0.09	0.37	0.05	0.32	0.20	-0.02	-0.20	-0.09	1

Source: Author`s calculations using Stata 19.

It is clear that the correlation coefficients are broadly similar across the two samples. This suggests that there should not be substantial parameter instability in the estimates. The main finding from the correlation analysis, however, concerns the existence of high pairwise correlations between initial equity-adjusted income and both of our human capital proxies. This means that including all three variables in the same specification would likely produce unreliable results. To avoid this issue, we perform auxiliary ordinary least squares (OLS) regressions of each human capital proxy on initial equity-adjusted income. The residuals from these regressions, which we use in our subsequent modeling, provide the variation in education or health that is not explained by initial equity-adjusted income. Interestingly, both regressions show significant effects of initial equity-adjusted income on both human capital proxies (full results are available upon request). The other independent variables do not warrant any modification, as they do not exhibit strong correlation patterns.

Table 4 reports the BMA results for both the basic and the upgraded sample. In both cases, a uniform model prior has been selected, along with Zellner's g-prior for the coefficient estimates. All calculations were performed using the Stata 19 software package. As some observations had to be discarded due to missing data, the last row reports the effective sample size, which is lower than the initial sample size in both samples.

Table 4. BMA estimation results on both samples (inclusive growth)

Dependent variable: inclusive growth	**Basic sample**			**Upgraded sample**		
Independent variables	**Mean**	**St. dev.**	**PIP_k**	**Mean**	**St. dev.**	**PIP_k**
Log(initial soc mob index)	-1.343	0.255	0.99991	-1.145	0.228	0.99972
Log(fixed cap form)	3.122	1.600	0.86906	2.371	1.328	0.83661
Log(yrs of schooling) res	0.669	1.514	0.2098	0.023	0.307	0.043253
Life expectancy at birth res	0.001	0.026	0.050855	-0.000	0.016	0.4207
Log(population growth)	-1.071	1.070	0.57244	-1.891	0.882	0.89626
Log(inflation)	0.028	0.208	0.052996	-0.02	0.146	0.054621
Central government debt	0.000	0.002	0.0513	-0.001	0.003	0.084135
Trade openness	0.013	0.004	0.98407	0.012	0.004	0.98462
Constant	5.650	5.056	1	7.195	4.595	1
Effective sample size	546			667		

Source: Author`s calculations using Stata 19.

As expected, initial equity-adjusted income has been identified as the most robust determinant of inclusive growth in both samples. Echoing the convergence findings from economic growth studies, initial equity-adjusted income has been found to negatively affect the rate of inclusive growth. Fixed capital formation is somewhat less robust in terms of PIP, but it has a stronger positive posterior mean coefficient estimate. Among the other variables, only trade openness and population growth have PIP values above 50 percent. With a PIP consistently above 90 percent, trade openness has been identified as a positive determinant of inclusive growth, while population growth has been shown to negatively affect inclusive growth, albeit at a significantly lower level of robustness. Inflation and central government debt fail to show robust effects in either sample.

As for our human capital proxy variables, the BMA estimation does not reveal any robust effects of either the health or the education variable on inclusive growth. Yet, the effect of education is markedly stronger and positive in both samples, even surpassing a PIP value of 0.2 in the basic sample. The effect of health, however, hovers around zero in both samples, with strikingly low PIP values.

Even though our analysis does not reveal robust effects of the human capital variables on inclusive growth rates, our earlier correlation and regression analyses of the relationship between initial equity-adjusted income and the human capital proxies suggest that a more meaningful relationship may exist between these variables and equity-adjusted income in levels or logs. Because inclusive growth is defined in our framework as the growth rate of equity-adjusted income, examining the log of equity-adjusted income should be viewed as a complementary step within the same conceptual framework rather than as a departure from it. This allows us to assess whether human capital is more strongly associated with cross-country differences in the level of equity-adjusted income than with variation in its growth rate. For these reasons, we perform a BMA analysis using the log of equity-adjusted income as the dependent variable and the variables from Table 2, excluding initial equity-adjusted income, as the independent variables. The estimation results from this analysis are presented in Table 5.

Table 5. BMA estimation results on both samples (log of equity-adjusted income)

Dependent variable: log(equity-adjusted income)	**Basic sample**			**Upgraded sample**		
Independent variables	**Mean**	**St. dev.**	**PIP_k**	**Mean**	**St. dev.**	**PIP_k**
Log(fixed cap form)	0.003	0.020	0.056983	0.000	0.014	0.040848
Log(yrs of schooling)	1.776	0.069	1	1.766	0.070	1
Log(life expectancy at birth)	7.589	0.266	1	7.194	0.282	1
Log(population growth)	-0.002	0.014	0.057241	-0.001	0.012	0.041163
Log(inflation)	0.051	0.062	0.4672	0.015	0.034	0.20716
Central government debt	0.000	0.000	0.056967	-0.000	0.000	0.35386
Trade openness	0.002	0.000	1	0.002	0.000	1
Constant	-27.879	1.152	1	-26.000	1.183	1
Effective sample size	596			748		

Source: Author`s calculations using Stata 19.

It is now quite clear that the BMA estimates for both samples show highly robust effects of both human capital proxies on the log of equity-adjusted income. Both proxies exhibit an almost certain probability of inclusion, as well as strong positive effects. Besides these, a robust positive effect is identified only in the case of trade openness. The other variables have PIP values below 50 percent, suggesting a lack of robustness. These findings generally indicate that the human capital variables have more of a long-term effect, particularly in explaining what distinguishes countries with high levels of equity-adjusted income from those with lower levels.

It is important to note that, in the above regression, we transformed the health variable into logarithmic form in order to obtain a comparable elasticity-based interpretation for both variables. This enables a more adequate structural channel decomposition of the effects of the different proxies. To perform such a decomposition, we first need to obtain coefficient estimates for the two variables that constitute equity-adjusted income. In Table 6, we begin with the log of GDP per capita as the first component of equity-adjusted income. To ensure comparability of results, we keep the same explanatory variables, in the same form, as those used in the BMA estimation reported in Table 5.

Table 6. BMA estimation results on both samples (log of GDP per capita)

Dependent variable: log(GDP per capita)	**Basic sample**			**Upgraded sample**		
Independent variables	**Mean**	**St. dev.**	**PIP_k**	**Mean**	**St. dev.**	**PIP_k**
Log(fixed cap form)	0.001	0.013	0.04383	-0.258	0.062	0.9965
Log(yrs of schooling)	1.340	0.062	1	1.277	0.066	1
Log(life expectancy at birth)	7.011	0.237	1	7.512	0.247	1
Log(population growth)	0.002	0.014	0.060784	0.002	0.013	0.046286
Log(inflation)	0.096	0.058	0.81099	0.002	0.012	0.057401
Central government debt	-0.000	0.000	0.046447	-0.002	0.000	0.99959
Trade openness	0.002	0.000	1	0.001	0.000	0.99989
Constant	-23.693	1.026	1	-24.611	1.016	1
Effective sample size	616			780		

Source: Author`s calculations using Stata 19.

In line with other empirical growth studies (Barro, 2013; Bloom et al., 2004; Mankiw et al., 1992; Hanushek & Kimko, 2000), our findings reveal that the effects of both human capital proxy variables are positive, strong, and highly robust in both samples. The estimated effects of both human capital proxies are broadly similar to those from the equity-adjusted income analysis, suggesting that the effects of both variables on equity-adjusted income are transmitted primarily through the GDP per capita channel. This conclusion is further supported by the results of the BMA estimation using the log of the income equity index as the dependent variable. These results are reported in Table 7.

Table 7. BMA estimation results on both samples (log of income equity index)

Dependent variable: log(income equity index)	**Basic sample**			**Upgraded sample**		
Independent variables	**Mean**	**St. dev.**	**PIP_k**	**Mean**	**St. dev.**	**PIP_k**
Log(fixed cap form)	0.085	0.028	0.96923	0.183	0.020	1
Log(yrs of schooling)	0.391	0.025	1	0.461	0.021	1
Log(life expectancy at birth)	0.696	0.097	1	-0.002	0.022	0.042766
Log(population growth)	-0.082	0.016	0.99997	-0.054	0.017	0.97189
Log(inflation)	-0.001	0.006	0.068702	0.040	0.011	0.98602
Central government debt	0.001	0.000	0.99751	0.001	0.000	1
Trade openness	0.001	0.000	1	0.001	0.000	1
Constant	-4.879	0.384	1	-2.409	0.126	1
Effective sample size	596			748		

Source: Author`s calculations using Stata 19.

Mirroring the results from the previous BMA analyses, these findings mostly show robust and positive effects of the human capital proxies on the income equity index. While the BMA analysis for GDP per capita revealed a much stronger effect of the health variable in both samples, the results for the income equity index are less unambiguous. The analysis performed on the basic sample reveals somewhat stronger effects of health, whereas the effects of health are virtually non-existent in the upgraded sample. Education, however, exhibits significantly more consistent estimation results across samples.

Given that we observed robust and positive effects of the human capital proxies in log rather than in growth regressions, we modify the structural channel decomposition equation (7) so that it refers to equity-adjusted income, GDP per capita, and the income equity index in the following manner:

$$\alpha = \frac{\bar{\beta}_{gdppc}}{\bar{\beta}_{eai}};\ 1 - \alpha = \frac{\bar{\beta}_{iei}}{\bar{\beta}_{eai}} \qquad (8)$$

Here, $\bar{\beta}_{gdppc}$ and $\bar{\beta}_{iei}$ now stand for the BMA posterior coefficient mean estimates for the GDP per capita and the income equity index, respectively. $\bar{\beta}_{eai}$, by contrast, denotes the effect of the human capital proxies on equity-adjusted income, obtained by summing the effects of human capital on the two component variables. The parameters α and $1 - \alpha$ still refer to the relative importance weights of the effects of human capital on the two components of equity-adjusted income. Performing the structural channel decomposition using this formula yields the findings displayed in Table 8.

Table 8. Structural channel decomposition of human capital proxy effects

Proxies	Growth channels	Basic sample	Upgraded sample
Health	GDP per capita	90.97%	100%
	Income equity index	9.03%	0%
Education	GDP per capita	77.41%	73.48%
	Income equity index	22.59%	26.52%

Source: Author`s calculations using Stata 14.

The structural channel decomposition analysis unambiguously shows that the effect of human capital on equity-adjusted income is transmitted mostly through the GDP per capita channel, regardless of the proxy variable or sample chosen. The disproportionate nature of this transmission is much more evident in the case of the health proxy. In the basic sample, more than 90 percent of the effect of health on equity-adjusted income is transmitted through the GDP per capita channel. In the upgraded sample, this share rises to 100 percent, given that the effect of the health variable is not identified as robust in that case. Even though the estimated effects of the education variable are more nuanced, the GDP per capita channel dominates there as well. Its contribution ranges from around 73.5 percent in the upgraded sample to above 77 percent in the basic sample. This, however, still leaves some room for the redistributive effects of education, confirming the findings of earlier studies (Barro, 2000; De Gregorio & Lee, 2002).

It must be noted that the estimated total effects of the human capital proxies on equity-adjusted income reported in Table 5 do not exactly match the effects obtained by summing the separate estimates of their effects on GDP per capita and on the income equity index. These differences in estimates are shown in Table 9.

Table 9. Differences in estimated effects on the equity-adjusted income (absolute values)

Proxies	Basic sample	Upgraded sample
Health	0.118	0.318
Education	0.045	0.028

Source: Author`s calculations.

It can be seen that these differences are not large in magnitude, particularly in the case of the education proxy. In the case of both proxies, they may arise from a variety of factors, including noise resulting from differences in sample size and composition (Wooldridge, 2002). The larger absolute difference in the case of the health variable may be related to specific factors pertaining to health measurement in some countries, particularly the less developed ones included in the upgraded sample. The same factors may also explain the unexpectedly estimated zero effect of health on the income equity index in the upgraded sample. Investigating these issues is beyond the scope of this paper and represents a topic for further research.

CONCLUSION

In this paper, we furthered the empirical assessment of the determinants of inclusive growth using the concept developed by Anand and colleagues (2013). More specifically, we focused on estimating the effect of human capital proxies, namely the education and health dimensions, on inclusive growth, understood as the growth rate of equity-adjusted income, as well as on equity-adjusted income itself as the underlying level variable. This focus is reasonable, given that at least some human capital proxies have been found to be statistically significant contributors to both components of equity-adjusted income: real GDP per capita growth and income equity growth. To do so, we employed the Bayesian Model Averaging (BMA) approach.

Our findings show that both education and health exhibit robust and positive effects on equity-adjusted income as a log variable, while having no robust effect on inclusive growth rates as originally defined. Moreover, we conducted a structural decomposition of the effect of human capital on these two components in order to identify the primary transmission channel of that effect. We found that both human capital proxy variables primarily affect equity-adjusted income through the GDP per capita channel. In the case of health, the relative contribution rises above 90 percent, while in the case of education, it lies around 70–80 percent. This suggests that education also exerts a meaningful influence through the income equity index channel.

In this way, the paper addresses a specific gap in the literature. Although earlier research has identified human capital as an important determinant of inclusive growth, as well as of its growth and distributional components considered separately, it has not explicitly examined through which of these two channels the overall effect of human capital on equity-adjusted income is primarily transmitted. Nor has it clearly distinguished between effects on inclusive growth rates and effects on the underlying level variable itself. The main contribution of this study is therefore to provide such an assessment within a BMA framework, while also complementing it with a structural decomposition of effects. In doing so, the paper adds to the existing literature by showing that the influence of human capital on equity-adjusted income operates predominantly through the GDP per capita channel, while also indicating that education retains a non-negligible role through the income equity channel.

Even though our paper has produced interesting and insightful results, there are significant shortcomings and avenues for further research that should be pointed out. First of all, our measure of inclusive growth, championed by Anand et al. (2013), may need to be modified, particularly in order to account for certain normative considerations. In its current form, this measure allows morally problematic outcomes to be counted as instances of inclusive growth. A good example would be a case in which the two or three highest income deciles experience relatively significant gains, while some of the lowest deciles lose a relatively small amount of income. To address this issue, it may be necessary to refine the measure proposed by Anand et al. (2013) into a rank-weighted metric, as Donaldson and Weymark (1980) did for income inequality indices. It would be particularly relevant to examine whether the relative contribution values change as a result of introducing such rank-weighted metrics.

Furthermore, there is a need for a much more extensive treatment of model uncertainty, endogeneity, and dynamics. Even though the incorporation of the BMA approach addresses model uncertainty to a certain extent, a much wider set of variables, made feasible by model-sampling techniques, should be considered in order to confront model-uncertainty issues more fully. In the context of endogeneity and dynamics, it would be preferable to apply the LIBMA methodology directly to our chosen set of variables. Resorting to control variables that have been established as robust growth determinants by earlier research is a decent initial step, but more is needed, particularly since inclusive growth is much more than mere GDP per capita growth.

Finally, future research should focus on policies aimed at strengthening those dimensions of human capital that are most conducive to improvements in equity-adjusted income and, more broadly, inclusive growth. One such policy could involve increasing public expenditure on education (Tomić, 2015), while simultaneously placing greater emphasis on the efficient allocation of resources. It is highly likely that, without an appropriately designed and implemented policy framework, the transition toward a high-human-capital environment would become considerably more difficult and uncertain.

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