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WIDER Working Paper 2015/093

Inferring the economic standard of living and health from cohort height

Evidence from modern populations in developing countries

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September 2015

United Nations University World Institute for Development Economics Research

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Abstract: Average adult height is a physical measure of the biological standard of living of a population. While the biological and economic standards of living of a population are very different concepts, they are linked and may empirically move together. If this is so, then cohort heights can also be used to make inferences about the economic standard of living and health of a population when other data are not available. We investigate how informative this approach is in terms of inferring income, nutrition, and mortality using data on heights from developing countries over the last 50 years for female cohorts born 1951-1992. We find no evidence that the absolute differences in adult height across countries are associated with different economic living standards. Within countries, however, faster increases in adult cohort height over time are associated with more rapid growth of GDP per capita, life expectancy, and nutritional intake. Using our instrumental variable approach, each centimeter gain in height is associated with a 6% increase in income per capita, a reduction in infant mortality of 7 per thousand (or an 1.25 year increase in life expectancy), and an increase in nutrition of 64 calories and 2 grams of protein per person per day relative to the global trend. We find that increases in cohort height can predict increases in income even for countries not used in the estimation of the relationship. This suggests our approach has predictive power out of sample for countries where we lack income and health data.

Keywords: height, standard of living, inference, economic development
JEL classification: O10, O47

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This study has been prepared within the UNU-WIDER project on 'Health and Development'.

ISSN 1798-7237 ISBN 978-92-9230-982-4

Typescript prepared by the authors.

UNU-WIDER gratefully acknowledges the financial contributions to the research programme from the governments of Denmark, Finland, Sweden, and the United Kingdom.

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1 Introduction

In addition to genetic heritage, individual adult height depends on physical growth during childhood and adolescence, which in turn depends on childhood nutrition, energy use, and experience of disease. Evidence on the genetic component of height come from twin studies and Genome-Wide Association meta-analysis (Jelenkovic et al 2011, Lango Allen et al 2010, Soranzo et al 2009). Studies have estimated the effects of early childhood environmental conditions, such as income, nutrition, and disease on adult heights (Steckel 2008, 1995, 1986, Fogel 1994, Alderman, Hoddinott and Kinsey 2006, Akachi and Canning 2007). The sensitivity of adult height to childhood living conditions has led to the use of height as a measure of the "biological standard of living" in economic history when studying populations for which more conventional measures of living standards are absent (Komlos and Baten 2004). Data on adult heights are sometimes available from historical sources for populations for which height was measured and recorded, and height can also be estimated from skeletal remains (Steckel, Sciulli and Rose 2002).

In addition, heights can be used to compare living standards between modern populations in different countries such as those between the two Koreas and two Germanys (Pak 2004, Komlos and Kriwy 2003, Komlos 2001) or within countries over time (Steckel and Floud, 1997, Komlos 1993, Lopez-Alonso and Condey 2003) and to study inequality and the relative living standards of subgroups within countries (Moradi and Baten 2005, Deaton 2008, Margo and Steckel 1982). Pak (2004) for example, shows that while both South Korea and North Korea had similar adult height for cohorts born in 1940, the adult height in North Korea has stagnated while that of South Korea has increased by 6 cm since then. Steckel (2013) provides a recent survey of the field. This approach uses adult height as an independent indicator of the standard of living that is thought to be correlated with, but different from, income per capita and other measures of living standards.

Nevertheless, if adult height and other measures of the standard of living are correlated, we can potentially make inferences about income per capita, nutrition, and disease burdens in populations from observations of adult height alone when direct evidence on these variables is not available. Baten and Blum (2012) estimate a relationship explaining income per capita with adult height data for decade averages in a large panel of countries over more than a century, finding a positive relationship. This suggests that tall adults are associated with a higher level of income per capita. Their approach takes income per capita as the dependent variable, and adult height as the independent variable, in a regression analysis which reverses the usual approach and assumed direction of causality.

Can we use variations in height to draw inferences about changes in health, nutrition, and income levels? Komlos (2001, 1993) has stressed that height is a proxy for the "biological standard of living," and is different from measures of the economic standard of living; while it is different it may still provide valuable information on economic living standards when other data is not available. The contribution of this paper is that by focusing on the second half of the 20th century, we enable comparisons of adult height to measures of the economic standard of living and health such as income, nutrition, infant mortality rate, and life expectancy for developing countries and therefore study how well we can infer these indicators from height data alone. Reliable sources of data only became available for the last several decades in the panel data format, and we provide evidence that average cohort height can be used to infer income and other indicators of interest when direct evidence on economic living standards and health are missing.

2 Data

The data sources for our cohort height variable are Demographic and Health Surveys (DHS). For each country, we use the latest available DHS. The typical DHS dataset measures the height of women from age 15 to 49. Not every DHS dataset includes height of all women as some have no data on heights while others only have height of mothers (women who have given birth in the last five years). Including surveys with only mothers would create a sample selection problem; for example, if height is positively linked, while fertility is negatively linked, to socioeconomic status, mothers will be shorter than average. We do not use data from surveys where only mothers' height is measured. It could be argued that the bias introduced by including countries with height measurements only for women who have given birth in the last five years is small. Moradi (2010) shows that in the DHS samples from 16 sub-Saharan African countries, around 59% of women aged 20-50 have given birth in the last 5 years. Based on countries where there is complete data, constructing height estimates only from these mothers does lead to a downward bias. This bias is very small, and could be regarded as negligible. Nevertheless, our study also includes countries from Latin America and Asia, where the fertility rates have been substantially lower, and more rapidly changing, than in sub-Saharan Africa. Across the countries considered, these empirical relationships might well vary if they are at different stages of demographic transition. It may be that the selection effect in these regions is both larger and time varying. We prefer to exclude these mother only samples from our analysis rather than risk the potential selection bias.

Each survey is checked country by country, and all available DHS dataset with height of all women are included in the analysis. This gives us a sample of 38 countries. These countries are listed in Table 1. We use the latest survey available in each country to provide our primary dataset. We extract heights of women only from age 20 and above on the grounds that at age 20, physical development has likely ceased. After age 50 a decline in physical stature is likely to occur with aging (Fernihough and McGovern 2013). The number of observations in a typical DHS dataset is around 4,000, though there is variation in sample size by age within a survey as well as across countries and time. Height, without shoes, is measured in DHS surveys by the interviewer, using a headboard. While this is an objective measure (rather than a self-report), there may still be measurement error in individual observations. Extreme heights (defined as below 100 cm and above 250 cm) were excluded from the sample as well as a small portion of missing observations. Our calculation of cohort height also has error due to the fact that it is based on a sample rather than the whole population. Though our data are nationally representative samples, the probability of being sampled is usually unequal for different observations, and we use the sampling weights provided in the survey to construct estimates of average adult height for each country by birth year.

We also list, where available, the data from an earlier survey for these countries in which the heights of all women in the age range (not just mothers) was measured. These earlier surveys are usually about 5 years before the latest survey and provide similar height data for overlapping cohorts. Since each DHS survey draws a different random sample of the population, these earlier surveys give height estimates for some of the same cohorts with sampling error that is independent of that found in the latest survey. We use these independent cohort height estimates as instruments to overcome the problem of measurement error (they are correlated with the measured cohort height in the main sample but uncorrelated with the measurement error in that sample).

Some recent DHS surveys also collect height data on a subset of men in the sample. These data, however, covers substantially fewer countries than for females, with a smaller sample size within each country, and we do not use it in our analysis. Nevertheless this may be a promising line of inquiry given that male physical growth may be more sensitive to environmental conditions, such as nutrition, than female growth (Hamilton 1982). We emphasize the fact that we use data on women because almost all historical studies to date, and particularly those which have examined the relationship between height and income, are based on men. One could hypothesize that the relationship would differ between genders, particularly in developing countries where the bulk of the population is engaged in heavy manual labor, or where childbirth still represents a significant risk for the women of childbearing age which are represented in the data. This could yield differences in the height-income relationship and any comparison between this study and the past studies using data on men may be impaired. Studies so far have found that there is limited evidence that the relative gap between male and female height widens as living conditions and human stature increase (Jelenkovic et al 2011, Lango Allen et al.,2010; Soranzo et al.,2009, Gustafsson and Lindenfors 2004).

Table 1 describes the number of women with height data per DHS, the initial and last birth year of the cohort heights, mean and standard deviation of height of all individuals in each survey. Using the individual level data on height we construct the average height of each birth cohort by year in each country. The average cohort height data we constructed are based on a total of 773,661 individual observations. On average we have 653 women per birth year in each country. 1184 annual cohort heights were constructed from the latest DHS in addition to the 791 cohort heights from the prior DHS which were used for the instrumental variables approach. Birth years for the 1184 cohorts are from year 1951 to 1992 and the ages of individuals range from 20 to 51 (Table 2). We compare these average cohort heights with indicators for health, nutrition, and income for the country in the year the cohort was born.

For income per capita we use GDP per capita from Penn World Table 7.0 (PWT 7.0) using PPP Converted Gross Domestic Income (RGDPL adjusted for Terms of Trade changes) at 2005 constant prices. While we focus on GDP per capita as a measure of living standards, there is a real issue of whether it does accurately capture wellbeing. This is in part because it excludes non-traded goods, such as leisure, and even of traded goods the reduction of the different consumption patterns in different countries to a single common unit raises perhaps insurmountable problems of aggregation (Deaton 2010).

For life expectancy and the infant mortality rate, we use the World Bank's World Development Indicators (2012), which gives data back to 1960. We use the life expectancy at birth for females since this should match more closely the female height data than overall life expectancy. The infant mortality rate is the number of children who die before reaching age one, per 1,000 births.

For nutrition we use daily average consumption of calories and protein from the Food and Agriculture Organization (FAO) (2012) FAOSTAT database, with data going back to 1961. The FAO food balance sheets provide information on food supply at the population level, estimated on the basis of the annual food production, imports, and exports, changes in stocks, agricultural and industrial uses within a country, as well as losses during storage and transportation (Naska et al 2009). Jacobs and Sumner (2002), discuss the construction of the food balance sheets, problems in constructing the data, and their appropriate use. Calories and protein consumed per capita are calculated from national consumption of each foodstuff using nutritional tables of calorie and protein content, and dividing by the population.

Table 2 shows descriptive statistics for the country-cohort level data we use. We report descriptive statistics for average cohort height measured in centimeters, log GDP per capita in 2005 international dollars, the infant mortality rate per 1,000 births, average calorie intake per person per day, and the average protein intake measured as grams per person per day, and female life expectancy in years. Table 3 shows pairwise correlation coefficients of residuals among the variables, after running regression with year dummies and country fixed effects. Height is, as expected, negatively correlated with infant mortality and is positively correlated with both calories and protein consumption as well as with income per capita and life expectancy. Our two nutrition variables, calorie and protein intake were highly correlated (ϱ= 0.85). The infant mortality rate and female life expectancy were moderately correlated (ϱ= - 0.57).

3 Methods

We estimate the relationship between income and height with height as the dependent variable starting with simple ordinary squares regression. We run our model with country fixed effects and year dummies to account for unobserved exogenous factors such as genetic heritage. In the fixed effects approach, we are trying to model variation in average heights from the national average. In doing this, the signal to noise ratio (with the noise being due to measurement error) is lower than in the pooled model where we are also explaining the differences in heights across countries. We also use an instrumental variable approach to adjust for measurement error in population height. In addition to income, we also explore other measures of living standards such as infant mortality rate, nutrition intake, and life expectancy. STATA13 is used as the statistical software of our choice to fit the models, and for our main result, IVREG2 command was used. Further details on the theoretical structure of correlations between height and income and inference from height are included in the Appendix as Theory.

4 Regression results

We investigate whether height can be used to draw inferences about changes in other measures of biological and monetary standards of living. We begin by attempting to explain GDP per capita in our sample of countries with the height of the cohort that was born the same year as the income measurement. The results are reported in Table 4. In column 1 of Table 4 we report a simple pooled ordinary least squares regression. In this regression, the coefficient on height was negative and statistically significant. The fixed effects in the determinants of height (Akachi and Canning 2007, 2010) suggest that there should also be a fixed effect in our regression explaining income levels; cross country variations in height not associated with health and nutrition may not be related to the income level. The fixed effects, added to the regression in column 3, improves the fit of the regression dramatically and makes the coefficient on height positive.

There is, however, a problem of measurement error with using cohort average heights as an indicator of living standards. If average heights are constructed using small samples of individuals, the cohort height will contain measurement error. This will bias the estimated coefficients in our regression downwards since most of the variation in measured average height may reflect sampling variation, which has no consequences for expected income, as opposed to actual movements in the population's average height.

We can reduce the measurement error to some extent by averaging heights over several years to increase the number of observations in the average, but this will still leave some sampling error. Instead we use an instrumental variable approach, instrumenting a cohort's estimated average height with the height of the same cohort as measured from a previous DHS survey in the country. The average height of sample in the previous survey is clearly correlated with the mean of the sample we are instrumenting. More importantly the measurement error due to sampling is independent in each survey so that instrumenting will overcome the bias and inconsistency in our results due to measurement error (Hausman 2001).

Columns 2 and 5 of Table 4 report the results when the average cohort heights are instrumented with independent estimates based on previous surveys. This reduces our sample size somewhat due to the need to have data on a cohort from both surveys. In the case of the pooled model, instrumentation makes little difference. However when we use fixed effects, the ratio of noise (due to sampling variations) to information (reflecting real movements in cohort height) is large and instrumentation increases the estimated coefficient on height dramatically. In column 5 of Table 4 we estimate that each extra centimeter of cohort height is associated with a 6% increase in income per capita.

The first-stage regressions of the two-stage least squares models from Table 4 Columns 2 and 5 are shown in Table 5. In these first stage regressions the dependent variable is the average cohort height as measured in the latest DHS survey. In the case of the pooled model the coefficient on the instrument, the average height of the cohort as measured in the previous survey is close to one. However, in the fixed effect model, the coefficient on the instrument is much smaller, around one third.

While instrumentation overcomes the measurement error in theory, in practice the estimated coefficients can still be biased if the instruments are weak (Murray 2006). This is in the sense they are not highly correlated with the variable being instrumented. We report the Cragg-Donald F statistics for weak instruments for both our first stage regressions. In both cases the value is above the critical value for a bias of no more than 10% reflecting the fact that our instrument is highly predictive.

Moreover in Column 4 of Table 4, we report the country fixed effects model with 5-year averages instead of the two stage least squares model to see whether the result changes due to measurement errors and age misreporting. The result remains robust, but we lose power by bundling the number of observations by 5 years.

Our preferred specification is given by Column 5 in Table 4 with the first stage in Column 2 of Table 5. The relationship between cohort height and log income per capita is modified by country fixed effects and time dummies. We allow for time dummies in the relationship between cohort height and income per capita. Several factors affect cohort height, including nutrition and the disease environment. The time dummies capture secular trends in these omitted variables. If data is available on these omitted variables, their inclusion would improve the model fit. In this paper, however, we are interested in the power of height on its own right to predict other indicators of the standard of living. In Table 6, we report the result of similar two stage regressions with different measures of health and nutrition as outcomes. Note that equation (9) in our theory section allows us to estimate the expected value of each of these outcomes based on height income of about 1% a year, independent of height. Each centimeter in height gain is associated with a 6.2% gain. The first stage of each regression in Table 6 is the same as in Table 5 Column 2, with minor variations due to missing observations on the outcome variables and slightly different samples.

In terms of health, we find that each centimeter gain in cohort height is associated with an increase of about 1.25 years in life expectancy and a reduction in infant mortality of about 7.4 children per 1000 births. Baten and Komlos (1998) analyzed the height data for birth cohorts from 19th to 20th centuries and concluded that every centimeter above and beyond a given population's average height translates into a life-expectancy increase of 1.2 years, which is very close to our result. For nutrition, a gain in a centimeter of height is associated with an extra intake of 64 calories per person per day and an extra intake of protein of about 1.7 grams per person per day. Appendix-Tables 1-4 shows the full set of regressions for each of these outcomes variables following the same format as Table 4 for log GDP per capita. In each case we use Column 5 of the appendix table as our specification and report it in our summary of results in Table 6. In each case in Table 6, height does predict the living standard we use as dependent variable and has a coefficient that is significantly different from zero at the 5% (or even 1%) level.

In addition, we tried adding continent dummies (Africa, Asia, or Latin America) as alternative to country fixed effects and run the same set of regressions. The results are shown in Appendix-Table 5. Analyzing separately by continents resulted in losing much of the sample size and significance. Even for Africa which had the largest sample, we could not find a statistically significant effect. Both Asia and Latin America appear to have higher income per capita and life expectancy, and lower child mortality than Africa, conditional on adult heights. The coefficients on height become smaller when continent dummies are included instead of country fixed effects, but they remain significant for every dependent variable. Nevertheless, when the country fixed effects are added in addition to continent dummies they are still significant (jointly and often individually), indicating that continent dummies do not capture all the cross country variation. We therefore prefer the model with country fixed effects.

5 Discussion

Contrary to the results in Baten and Blum (2012) we find that cohort height does not predict the level of income per capita, or other living standards, across countries. Countries in which people are tall do not appear to be any richer, better fed, or healthier, on average. This is most likely an issue of different samples. Our sample of countries is limited to developing countries while Baten and Blum also include developed countries. In our sample the gaps in income levels across countries are fairly small compared to the Baten and Blum sample, and it is likely that other factors, such as genetic variation, overwhelm income effects in our data. We focus only on developing countries as they are more likely to be comparable to the populations studied in economic history in which populations are much poorer than the present developed countries.

Our results suggest that in our sample of countries, there are unobserved exogenous factors that may affect the relationship between height and other living standards. Heights depend on a wide range of additional variables. An obvious possibility is that genetic differences, which are known to explain a large portion of the individual variation in height (Silventoinen 2003), also affect average heights across countries without affecting other outcomes, though other factors such as climate, culture (Blum 2013a) or a long intergenerational lag structure in the determinants of height may also play a role. It should also be noted that the individual variation in height due to genetics is distinctly different from the effect of genetic heritage on the average population height. Technological change may also lead to improvements in one aspect of the standard of living but not others. Moreover, de Beer (2012) emphasizes the importance of milk consumption. Baten and Blum (2014) extend this by showing the importance of lactose tolerance as a factor in population height. Bozzoli, Deaton and Quintana-Domeque (2009) and Hatton (2011) argue that mortality rates affect height, and this selection effect means high mortality countries may have taller survivors and measured heights. Inequality within the population may also affect height, and this is another potential difference between economic and biological standard of living metrics that we need to take into account in inferring one indicator from another (Steckel 1995, Blum 2013b). This highlights the importance of our Theory in the Appendix where we show that the estimates of the unconditional expectation of outcome variable given height are possible even with the exclusion of factors that affect height, or income, from the estimated relationship.

When we run our model with country fixed effects and year dummies to account for these exogenous factors, we find that taller cohort heights are associated with higher income and nutrition, and lower infant mortality. This means when a country has increasing adult heights, we can infer that it likely has increasing income per capita, improving nutrition and declining infant mortality.

In addition, to check the robustness of the result, we see if our methods work out of sample (Appendix Theory and Appendix Figures 1, 2, and 3). Varian (2014) argues that econometric models should routinely be validated by their ability to predict outcomes in a different sample from the one they are estimated on. We split our sample into two random groups of countries (19 countries in each group) and use our model to estimate the relationship between height and other measures of living standards from one set of countries and then apply this result to the other, the simulated out of sample group. This allows us to compare the predicted changes in living standards based on observed changes in height in one sample with the outcomes in the other sample. We find that the predicted values do forecast the actual income changes in our simulated out of sample set of countries. We repeat the analysis for a thousand random draws of in-sample and simulated out-of-sample prediction groups to show that the results are robust. The result is an improvement in prediction performance on average and not just for one random draw of countries. We therefore have evidence that **changes** in adult height for birth cohorts heights over time **within** a country do predict changes in measures of living standards in that country over the same time period, applying the estimates obtained from a different set of countries. This means we can use changes in cohort height to predict out-of-sample for developing countries.

6 Conclusion

Economic historians and others have used height as an indicator of living standards when other conventional indicators are unavailable. Komlos has emphasized that height could be a proxy for the "biological standard of living," and our research explores the association between monetary and biological measures of the standard of living. Within low and middle-income countries, we find that increases in height are associated with increases in GDP per capita, calories and protein intake, and life expectancy as well as declines in infant mortality. Our analysis suggests that average height can be used to draw inferences on health, nutrition, and income of the population; however, care must be taken.

Our model assumes a stable relationship between our variables of interest which appears to hold in our sample once we control for country fixed effects and time dummies. The need for country fixed effects means we cannot make inferences from differences in height across countries for our sample; one country may have a taller population than another but lower income per capita due to a different fixed effect. The significance of joined year dummies is also worrying for inference in historical data. In our sample we expect to see income growth, even in countries with no changes in adult height, due to the effect of the time dummies. If economic historians wish to argue that increases in height are associated with rising income, while reductions in height mean falling incomes, there must be no time effects in the relationship between income and height in the historical period, which may be true but is not obvious. What we can say from our study is that if one country has adult heights that are rising faster than in another country, the former is likely also seeing faster improvement in other measures of living standards in the same period. Pak (2004) shows that while both South Korea and North Korea had similar adult height for cohorts born in 1940, the adult height in North Korea has stagnated while that of South Korea has increased by 6 cm since then. Our results suggest that this height difference reflects differences in income, nutrition, and health between the two countries.

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Table 1: Demographic and Health Survey years and countries analyzed

Country	DHS survey year	Number of women	Initial birth year	Last birth year	Mean height	SD of height
Bangladesh	2011	15,450	1961	1991	150.89	5.50
Bangladesh	2007	9,519	1957	1987	150.57	5.49
Benin*	2006	14,030	1956	1986	159.05	6.59
Benin*	2001	5,006	1951	1981	158.50	6.23
Bolivia*	2008	13,450	1958	1988	152.09	5.94
Bolivia*	2003	13,591	1953	1983	151.78	5.92
Burkina Faso*	2010	6,797	1960	1990	161.83	5.90
Burkina Faso*	2003	9,696	1953	1983	161.65	6.14
Cambodia*	2010	7,417	1960	1990	152.74	5.47
Cambodia*	2005	6,571	1955	1985	152.37	5.37
Cameroon	2011	6,038	1961	1991	160.42	6.66
Cameroon	2004	4,005	1954	1984	160.17	6.22
Colombia*	2010	37,066	1960	1990	155.35	6.29
Colombia*	2005	29,819	1954	1985	155.20	6.22
Congo, Dem. Rep.	2007	4,731	1957	1987	157.19	7.93
Congo, Rep.*	2011-12	4,494	1961	1992	158.58	6.25
Congo, Rep.*	2005	5,431	1955	1985	158.86	8.11
Cote d'Ivoire*	2011-12	3,827	1962	1992	159.07	6.26
Cote d'Ivoire*	1998-99	2,318	1950	1979	159.84	6.20
Egypt, Arab Rep.	2008	15,990	1958	1988	159.47	5.93
Egypt, Arab Rep.	2005	18,671	1955	1985	158.51	5.62
Ethiopia	2011	12,280	1961	1991	157.03	6.59
Ethiopa	2005	5,099	1955	1985	157.52	6.61
Ghana	2008	3,838	1958	1988	159.27	6.58
Ghana	2003	4,435	1953	1983	159.13	6.59
Guinea*	2005	3,962	1955	1985	158.81	6.42
Haiti	2012	7,110	1962	1992	159.30	6.24
Haiti	2005-2006	4,120	1956	1986	158.73	6.47
Honduras*	2011-12	17,215	1961	1992	153.01	6.38
Honduras*	2005-6	15,515	1955	1986	152.19	6.40
India	2005-6	98,872	1956	1986	152.18	5.93
India	1998-99	78,169	1950	1979	151.18	5.65
Jordan*	2012	7,045	1957	1992	157.70	5.83
Jordan*	2007	5,114	1952	1987	158.25	6.51
Kenya	2008-9	6,892	1958	1989	159.33	7.40
Kenya	2003	6,213	1953	1983	159.84	6.42
Lesotho*	2009	3,002	1960	1989	157.29	6.38
Lesotho*	2004	2,571	1955	1984	157.42	6.64
Liberia	2007	5,872	1957	1987	157.12	6.30
Madagascar	2008-09	6,722	1959	1989	154.00	5.98
Madagascar	2003-04	6,573	1954	1984	154.22	5.92
Malawi	2010	5,927	1960	1990	156.36	6.41
Malawi	2004	8,869	1954	1984	156.07	6.28
Mali*	2006	11,440	1956	1986	161.31	6.66
Mali*	2001	10,140	1951	1981	161.63	6.17
Morocco*	2003-4	13,988	1953	1984	158.54	5.92

Mozambique	2011	10,572	1961	1991	156.30	6.25
Mozambique	2003	9,306	1953	1983	155.96	6.24
Namibia	2006-07	7,762	1957	1987	160.58	7.03
Nepal*	2011	4,786	1960	1990	151.51	5.67
Nepal*	2006	8,313	1956	1986	150.91	5.48
Nicaragua	2001	9,671	1951	1981	153.88	6.10
Nicaragua	1998	10,019	1950	1978	153.94	6.09
Niger*	2006	3,680	1956	1986	160.78	6.00
Nigeria*	2008	26,356	1958	1988	158.17	7.26
Nigeria*	2003	5,873	1953	1983	158.64	6.59
Peru*	2012	19,227	1962	1992	151.94	5.69
Peru*	2007-8	21,996	1955	1988	151.44	5.70
Rwanda	2010	5,401	1960	1991	156.85	6.49
Rwanda	2005	4,408	1955	1985	157.41	6.42
Senegal	2010-11	4,389	1960	1991	163.09	6.76
Senegal	2005	3,500	1955	1985	162.97	6.64
Swaziland*	2006-7	3,890	1956	1987	158.92	6.31
Uganda	2011	2,074	1961	1991	159.42	6.44
Uganda	2006	2,254	1956	1986	158.98	6.53
Zambia*	2007	5,600	1957	1987	158.18	6.55
Zambia*	2001-02	6,060	1952	1982	158.05	6.25
Zimbabwe	2010-11	6,914	1960	1991	160.13	6.24
Zimbabwe	2005-06	6,710	1955	1985	160.16	6.15
Total		773,661				

Note: We use only surveys with height data of all women rather than just mothers. SD is standard deviation. *These countries were randomly chosen for estimation and the results were used to predict income based on height for those countries that are not marked by an asterisk as shown in Figure 3.

Source: DHS.

Table 2: Descriptive statistics of country level annual data

Variable	**Observations**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Average Cohort Height (centimeters) Latest DHS	1184	157.37	3.35	149.73	174.41
Average Cohort Height (centimeters) Prior DHS	791	156.84	3.56	149.54	164.42
Birth Year of the Cohorts Latest DHS	1184	1973.79	9.36	1951	1992
Age Latest DHS	1184	35.11	9.00	20	51
Log GDP (per capita)	1128	7.09	0.72	5.03	8.68
Infant mortality rate (per 1000)	1049	118.71	37.93	29.60	219.60
Calories (calories /day/person)	1093	2115.39	276.78	1487.00	3093.00
Protein (grams/day/person)	1093	53.36	10.11	29.90	82.10
Life expectancy (years)	1120	50.10	7.97	31.14	72.40

Note: Each average cohort height of a particular country is the mean height of the individuals born in the cohort year. SD is standard deviation across cohorts and not within.

Source: DHS, World Bank, FAO, PWT.

Table 3: Pairwise correlation coefficients of residuals

	Cohort Height	**Log GDP**	**IMR**	**Calories**	**Protein**	**Life expectancy**
Cohort Height	1.00 (1184)					
Log GDP	**0.16** (1128)	1.00 (1128)				
IMR	**-0.25** (1049)	**-0.37** (1029)	1.00 (1049)			
Calories	**0.17** (1093)	**0.43** (1066)	**-0.29** (1030)	1.00 (1093)		
Protein	**0.18** (1093)	**0.36** (1066)	**-0.23** (1030)	**0.84** (1093)	1.00 (1093)	
Life expectancy	**0.27** (1120)	**0.26** (1090)	**-0.56** (1049)	**0.29** (1093)	**0.21** (1093)	1.00 (1120)

Note: The pairwise correlation coefficients are for residuals from a regression of each variable on country fixed effects and year dummies. Correlation in **bold** are statistically different from zero at the 5% critical level. Number of observation is in parentheses.

Source: DHS, World Bank, FAO, PWT.

Table 4: Inferring income from cohort height (Dependent variable: Log GDP per capita, PPP adjusted)

	1	2	3	4	5
	Pooled OLS	Pooled Two Stage Least Squares	Country Fixed Effects	Country Fixed Effects 5-year Averages	Country Fixed Effects Two Stage Least Squares
Constant	12.20*** (1.23)	13.85*** (1.22)	1.54 (1.09)	-1.73 (2.32)	-3.24 (4.69)
Average Cohort Height	-0.029*** (0.006)	-0.039*** (0.008)	0.031*** (0.007)	0.054*** (0.015)	0.062** (0.031)
N	1128	773	1128	253	773
R-squared	0.035	0.075	0.942	0.949	0.951

Notes: Coefficients, standard errors in parentheses, significance level indicated as *(10%), **(5%), ***(1%). Panel data: each observation is for a (country, year). Year dummies added to all models except column 4 in which 5-year dummies were added. In the two stage least squares estimates average cohort height is instrumented with an independent measure of the average height of the same cohort from a previous DHS survey.

Source: Authors calculations based on DHS, World Bank, FAO, PWT data.

Table 5: First-stage estimates from the two-stage least squares models in Table 4 (Dependent variable: Average cohort height)

	1	2
	Pooled	Country Fixed Effects
Constant	4.24*** (1.44)	95.55*** (9.22)
Average Height cohort from previous survey	0.979*** (0.009)	0.374*** (0.061)
N	773	773
Centered R-squared	0.919	0.944
Cragg-Donald F statistic (weak identification test)	8157.75 (critical value 10% max IV size= 16.38)	50.05 (critical value 10% max IV size= 16.38)

Notes: Coefficients, standard errors in parentheses, significance level indicated as *(10%), **(5%), ***(1%). Year dummies added. The estimates in Column 1 above correspond to the 2nd stage in Column 2 of Table 4.The estimates in Column 2 above correspond to the 2nd stage in Column 4 of Table 4.

Source: Authors calculations based on DHS, World Bank, FAO, PWT data.

Table 6: Summary of regression coefficients for inferring the standard of living from cohort height:

Two-stage least squares results with country fixed effects

Dependent Variable	Coefficient of height	95% CI for the coefficient of height	N	R-squared
Log GDP per capita	0.062** (0.031)	[0.001, 0.122]	773	0.951
Life expectancy (years)	1.25*** (0.30)	[0.66, 1.83]	756	0.941
Infant mortality rate (per 1,000)	-7.39*** (1.66)	[-10.65, -4.14]	708	0.951
Calories (calories/day/person)	64.01*** (24.37)	[16.17, 111.85]	736	0.780
Protein (g/day/person)	1.70*** (0.64)	[0.45, 2.95]	736	0.882

Notes: Coefficients, standard errors in parentheses, significance level indicated as *(10%), **(5%), ***(1%). CI: Confidence Interval. All regressions contain country fixed effects and year dummies. Height is instrumented with height of the same cohort from a prior independent survey in the same country.

Source: Authors calculations based on DHS, World Bank, FAO, PWT data.

Appendix Theory

We begin by setting out a theoretical structure in which height and income are correlated and inference about income levels from heights is possible. We then show how to make inferences from adult height to income, or other measures of living standards, and finally apply our method to data from developing countries over the last 50 years. We have data on a range of variables for this period to see if the approach works in practice to allow us to infer income levels, nutritional status, and infant mortality rates from adult cohort height data alone.

We argue that, in theory, population height, income per capita, nutrition, and disease, and a host of other variables are part of a high dimensional simultaneous equation system with a complex pattern of causality between variables. If we assume that the relationships between these variables are stable across countries and over time, once we condition on observed exogenous factors, we have the potential to make inferences about one variable from knowledge of another. In particular, we show that if the structural model linking the variables in the system is linear and the error terms jointly multivariate normal, then the expected value of any unknown variable is a simple linear function of a known variable and the exogenous factors.

It follows from our theory that if we can estimate the linear relationship between two variables when both are known, we can expand this to give estimates of the unobserved variable when only one of the two is observed. The key result is that if cohort height is perfectly observed, a simple linear regression model gives the desired estimate of the relationship with other living standards. This is somewhat surprising given the well-known problems of estimating the structural model from observed data when causality runs in several directions. We are, however, not trying to estimate the causal effect of height on other outcomes but rather to seek the expected value of these other outcomes given data on height, which is a much easier task.

If we have perfectly observed data on heights, we can estimate the relationship between the outcome of interest and height (with height as the independent variable) using simple ordinary least squares regression and use the results to provide estimates of the outcome when it is not observed. In practice, however, population height is usually estimated from a sample of observations and hence contains measurement error. This will bias downwards our estimated coefficient on height in such a regression. We therefore adjust for this measurement error using an instrumental variable approach.

We apply our method to data from 38 low and middle income countries over the last 50 years predicting measures of living standards of the country in a particular year with the adult height of women born in that year. While adult height depends on environment throughout childhood, it is most sensitive to conditions around the time of birth (Akachi and Canning 2007). We limit ourselves to low and middle income countries because these are more likely to be similar to the populations seen in historical studies in which populations are usually much poorer than in developed countries today. We find that instrumenting the adult height can increase the size of the coefficient on height considerably, indicating that much of the variation in estimated cohort height is measurement error.

Consider a complex simultaneous equation system with a vector Y that defines an h dimensional set of endogenous variables, a vector X that defines a k dimensional set of exogenous variables. The time dimension is implicit. Suppose we have the structural model for each observation of the vector of endogenous variables in the matrix form

$$Y = AX + BY + \varepsilon \qquad (1)$$

We think of this as a set of structural equations relating all of the variables that interact in economic and social development. The endogenous variables in Y , which may include cohort height, income per capita, nutrition, and health measures, depend on the values of the exogenous variables and all the other endogenous variables which allow for feedbacks between the endogenous variables. We assume vector of error terms ε is multivariate normal and independent of the exogenous variables.

For simplicity we suppress the time subscripts in equation (1) but we think of all endogenous variables being measured at the same time. In principle there is no problem in adding lagged variables as additional components of the exogenous vector since these are predetermined. In the following section though, for simplicity, we consider only the relationship between the height of a cohort and the standard of living in its year of birth. In reality, while cohort height is most sensitive to conditions around the time of birth, it is also affected by conditions when the cohorts are adolescents and catch up growth is occurring (Akachi and Canning 2007). We leave the issue of making inferences based on these timing effects to later work.

The reduced form of the system where we write the endogenous variables as functions of the exogenous variables alone is:

$$Y = (I-B)^{-1}AX + (I-B)^{-1}\varepsilon = CX + u \qquad (2)$$

where

$$C = (I-B)^{-1}A \; and \; u = (I-B)^{-1}\varepsilon \qquad (3)$$

The new error vector u is a linear transformation of a set of multivariable normal variables and hence is multivariate normal. Further let S be the variance covariance matrix of ε then the variance covariance matrix of u is given by $V = (1-B)^{-1}S[(1-B)^{-1}]^{T}$. Let us now take two particular endogenous variables. Based on equation (2) we have that

$$\begin{aligned} Y_1 &= c_{11}X_1 + c_{12}X_2 + \ldots + c_{1k}X_k + u_1 \\ Y_2 &= c_{21}X_1 + c_{22}X_2 + \ldots + c_{2k}X_2 + u_2 \end{aligned} \qquad (4)$$

where (u_1, u_2) have a bivariate normal distribution. Suppose we know the true model in terms of the reduced form matrix C and the Variance Covariance Matrix V of (u_1, u_2) where

$$V = \begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{pmatrix} \qquad (5)$$

Then that conditional distribution $(Y_1 | X, Y_2)$ is normally distributed (see Bierens 2004) with mean

$$E(Y_1 | X, Y_2) = c_{11}X_1 + c_{12}X_2 + \ldots + c_{1k}X_k + E(u_1 | Y_2) \qquad (6)$$

where

$$E(u_1|Y_2) = E(u_1|u_2) = \sigma_{12}\sigma_{22}^{-1}u_2 = \sigma_{12}\sigma_{22}^{-1}(Y_2 - c_{21}X_1 + c_{22}X_2 + ... + c_{2k}X_2) \qquad (7)$$

and so

$$E(Y_1|X,Y_2) = (c_{11} - \sigma_{12}\sigma_{22}^{-1}c_{21})X_1 + (c_{12} - \sigma_{12}\sigma_{22}^{-1}c_{22})X_2 + ... + (c_{1k} - \sigma_{12}\sigma_{22}^{-1}c_{2k})X_k + \sigma_{12}\sigma_{22}^{-1}Y_2 \qquad (8)$$

or

$$\begin{aligned} &E(Y_1|X,Y_2) = \alpha_1 X_1 + \alpha_2 X_2 + ... + \alpha_k X_k + \gamma Y_2 \\ &\alpha_1 = c_{11} - \sigma_{12}\sigma_{22}^{-1}c_{21},\ ...,\alpha_k = c_{1k} - \sigma_{12}\sigma_{22}^{-1}c_{2k},\ \gamma = \sigma_{12}\sigma_{22}^{-1} \end{aligned} \qquad (9)$$

It follows that the best estimate of Y_1 given (X,Y_2) is this linear operator. We now turn to the estimation of the coefficients α_j and γ of this relationship. Again by Bierens (2004), $\omega = (Y_1|X,Y_2) - E(Y_1|X,Y_2)$ is mean zero, normally distributed and uncorrelated with (X,Y_2). Hence

$$(Y_1|X,Y_2) = \alpha_1 X_1 + \alpha_2 X_2 + ... + \alpha_k X_k + \gamma Y_2 + \omega \qquad (10)$$

has an error term that is mean zero, normally distributed and uncorrelated with all of the explanatory variables on the right hand side. It follows that we can estimate the parameters in equation (10) by ordinary least squares. If Y_2 is measured with error we can still get consistent estimates of this relationship by instrumenting Y_2 with a variable that is correlated with Y_2 but uncorrelated with the measurement error and ω.

There may be some disquiet about the estimation of equation (10) by ordinary least squares. Despite the demonstration that all of the assumptions of classical estimation are satisfied, Y_2 is an endogenous variable by construction, and it is well known that it is not possible to estimate the structural model given in equation (1) by ordinary least squares; the endogenous variables are clearly dependent on the error terms in equation (1).

Nonetheless, our approach is not aimed at recovering the underlying structural parameters in the matrices A and B. It should be clear from equation (8) that the estimated parameters in our regression depend on the correlation between the error terms as well as the structural parameters. We can regress one endogenous variable on another to get a predicted value, while not imposing any structure on the direction of causality or claim to be estimating a causal relationship. This is made clear in the following simple example where height is endogenous and has no causal effect on income.

Let income per capita be given by $Y_1 = \varepsilon_1$ and let height of the birth cohort in that year be given by $Y_2 = bY_1 + \varepsilon_2$ where $(\varepsilon_1, \varepsilon_2)$ are independently normally distributed with variances s_{11} and s_{22} respectively. Here it is clear that income per capita is exogenous and height depends on income. Since the system is triangular, we could estimate the second equation by ordinary least squares to find b, the effect of income Y_1 on height Y_2. This is the approach often used in studies of adult height. Suppose, however, we run the inverse regression

$$Y_1 = \gamma Y_2 + \omega = \frac{1}{b} Y_2 - \frac{1}{b}\varepsilon_2 \tag{11}$$

The OLS estimate γ in this regression does not converge to $1/b$ because Y_2 is correlated with $\omega = -\varepsilon_2 / b$. The OLS estimate is given by

$$\hat{\gamma} = (Y_2'Y_2)^{-1}(Y_2'Y_1) = [(b\varepsilon_1 + \varepsilon_2)'(b\varepsilon_1 + \varepsilon_2)]^{-1}(b\varepsilon_1 + \varepsilon_2)\varepsilon_1 \tag{12}$$

and it is easy to show that as the sample size becomes large we have that this estimate converges to the probability limit given by

$$p\lim \hat{\gamma} = \frac{bs_{11}}{b^2 s_{11} + s_{22}} \tag{13}$$

It follows that ordinary least squares applied to this regression does not give consistent estimates of the parameters of the structural model. However, the model has the form of a structural model as in equation (2) with A = 0 and

$$B = \begin{pmatrix} 0 & 0 \\ b & 0 \end{pmatrix} \tag{14}$$

that is:

$$\begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} = \begin{pmatrix} 0 & 0 \\ b & 0 \end{pmatrix} \begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} \tag{15}$$

hence by equation (2) the reduced form is $Y = (I - B)^{-1}\varepsilon$

$$\begin{pmatrix} Y_1 \\ Y_2 \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ -b & 1 \end{pmatrix} \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \end{pmatrix} = \begin{pmatrix} u_1 \\ u_2 \end{pmatrix} \tag{16}$$

where (u_1, u_2) is bivariate normal with variance covariance matrix

$$\begin{pmatrix} \sigma_{11} & \sigma_{12} \\ \sigma_{12} & \sigma_{22} \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ -b & 1 \end{pmatrix} \begin{pmatrix} s_{11} & 0 \\ 0 & s_{22} \end{pmatrix} \begin{pmatrix} 1 & 0 \\ -b & 1 \end{pmatrix}^T = \begin{pmatrix} s_{11} & bs_{11} \\ bs_{11} & b^2 s_{11} + s_{22} \end{pmatrix} \tag{17}$$

Hence by equation (8)

$$E(Y_1 | Y_2) = \sigma_{12}\sigma_{22}^{-1} Y_2 = \frac{bs_{11}}{b^2 s_{11} + s_{22}} Y_2 \tag{18}$$

And the OLS regressions of Y_1 on Y_2 is a consistent estimate of exactly the required coefficient on Y_2 to predict Y_1.

It is clear in this example that height does not cause income; variation in height due to shocks does not affect income. Yet, because income does affect height, the two variables are correlated, and we can exploit this correlation when we know height to predict income. An advantage of the theory is that it makes clear what is needed for inference. We do not need the entire set of endogenous variables in the system; we can make inferences about one based on information on any other. On the other hand, we do need to control for the observed exogenous factors in order to estimate equation(10). In practice we proxy these exogenous variables in our estimation with country fixed effects and time dummies.

Inference

The results in Table 6 give us some confidence that cohort height contains information that may allow us to make inferences about the standard of living of a population. When making inferences about the standard of living based on cohort height, there are two sources of potential error even if the model underlying our approach is correct. The first is that the reported coefficients on height in Table 6 are estimated and have sampling error. The second is that the measured cohort height will itself have sampling variation. It follows that if we want to construct confidence intervals for our predictions based on cohort height we should take both effects into account. We focus on the case of making inferences about log income per capita – the issues in other cases are similar.

We now turn to the issue of the variance of the predicted variable given an observed change in cohort height in a population; how certain are we of our prediction? This depends on two things, our uncertainty about the estimated parameter on height in our model, and uncertainty about the measured change in cohort height due to sampling variation.

Taking $\hat{\beta}$ to be the estimated coefficient on height from Table 6 and h_c to be the estimated cohort average height the expected effect on the outcome is $\hat{\beta}h_h$ assuming the two estimates are independent. The predicted income change given an observed change in height is $\Delta\hat{y} = \hat{\beta}\Delta\hat{h}$. Our estimate for $\hat{\beta}$ from Table 6 is 0.062. The exact variance (Goodman (1960)) of the predicted effect on income is

$$V\left(\Delta\hat{y}\right) = V\left(\hat{\beta}\Delta\hat{h}\right) = \hat{\beta}^2 V(\Delta\hat{h}) + (\Delta\hat{h})^2 V(\hat{\beta}) + V(\Delta\hat{h})V(\hat{\beta}) \qquad (19)$$

where the "hat" denotes an estimate. In practice, however, we do not know exactly the variance of the coefficient estimate or the estimate of cohort height. We can however get estimates of these using the standard deviation of the coefficient estimate from the regression, and estimating the sampling variation in average height based on the variance of individual heights and the size of the sample. We can then find an estimate of the variance of the predicted effect of a height change on income per capita (Goodman (1960)) by[1]

[1] Note the change in sign in the final term when we move from actual variances to estimated variances.

$$\hat{V}\left(\Delta\hat{y}\right) = \hat{V}\left(\hat{\beta}\Delta\hat{h}\right) = \hat{\beta}^2\hat{V}(\Delta\hat{h}) + (\Delta\hat{h})^2\hat{V}(\hat{\beta}) - \hat{V}(\Delta\hat{h})\hat{V}(\hat{\beta}) \qquad (20)$$

From the regression results in table 6 for income per capita as the dependent variable we have $\hat{\beta}^2 = 0.0038$ and $\hat{V}(\hat{\beta}) = 0.00096$. The values of $\Delta\hat{h}$ and $\hat{V}(\Delta\hat{h})$ depend on the country height estimates and the samples from which these estimates are based. If we assume a 6cm standard deviation in heights at the individual level within a cohort, which is approximately correct, and assume independent random samples of size n for both the initial and final cohort height estimates we can calculate that $\hat{V}(\Delta\hat{h}) = 2*36/n$. We use these numbers to calculate confidence intervals for the effect of an observed 1 centimeter gain in height on log income per capita and plot these for different values on n, the sample size for estimating heights, in Figure 1. For large sample sizes, in excess of 1000 observations for each cohort, we are fairly certain of the cohort average height and the uncertainty is mainly due to our uncertainty about β the relationship between height and income per capita. However for sample sizes smaller than 1000 we have considerable uncertainty as to what cohort height actually is and a corresponding large uncertainty in what we can infer about income per capita. One way to tackle this issue is to increase sample sizes for example by pooling cohorts over an interval of several years, at the cost of having less exact data on timing. An alternative is to look at changes in height over a long period of time so as to have large height changes which will increase the signal to noise ratio in the data.

The ordinary least squares results in Column 3 of Table 4 give the relationship between estimated cohort heights and income. The instrumental variable results in Column 5 give the relationship between actual cohort height and income. If we want to make inferences out of sample, and the survey design and sample sizes the estimated cohort heights are based are similar to those used in the estimation of the relationship, we should use the ordinary least squares results. We should only use the instrumental variable results if the out of sample estimates of cohort height are very accurate, for example if they are based on very large random samples. If the out of sample height estimates are based on very small samples they will be mainly sampling variation and we should give the little weight constructing inferences. Here we focus on splitting our sample in two and investigating if estimation on one half can help us make inferences on the other. Since in this case heights are all estimated from DHS data in which the number of observations in each cohort is similar, we use the ordinary least squares results in Column 3 of Table 4 as the basis of our inference.

The model underlying the estimates in Column 5 of Table 4 can be written as

$$y_{it} = f_i + \alpha_t + \beta h_{it} + \varepsilon_{it} \qquad (21)$$

Where f_i is a country fixed effect, α_t are year dummies, β is the coefficient on height and ε_{it} is an error term. Suppose we estimate the model on one set of countries but wish to obtain estimates for a different country or set of countries. The difficulty in this case is that we do not have estimates of the fixed effects for the new countries. However note that based on equation (21) we can take the "long difference" in income for a country between period 0 and period T to give

$$\begin{aligned} &\Delta y_i = \alpha T + \beta \Delta h_i + \Delta d\varepsilon_i \\ &where \quad \Delta y_i = y_{iT} - y_{i0}, \Delta h_i = h_{iT} - h_{i0}, \Delta\varepsilon_i = \varepsilon_{iT} - \varepsilon_{i0} \end{aligned} \qquad (22)$$

Without knowledge of the fixed effect we can say little about the level of income in a country. However using equation (22) we can estimate the average growth rate of income per capita over a period based on the change in height over the same period.

We can examine how well the model predicts economic growth by comparing the actual annual change in log GDP per capita and the predicted economic growth based on the Table 4 Column 5 model.

From these variables, we are able to estimate the actual and predicted annual average rates economic growth in income per capita based on our model in Table 4 Column 5. The result is plotted in Figure 2. The R-Square is only 0.11, indicating that while height changes can predict economic growth, there is a great deal more going on other than changes in height in relation to economic growth. The slope of the relationship between actual and predicated growth is close to one while the intercept is insignificant and close to zero. This is, however, not unexpected since we are using estimates based on this dataset to construct our predictions.

A sterner test is to look at the out of sample predictions of the model. We randomly divided our sample of countries into two halves with 19 countries in each sub-sample and estimated the model on one half and used the resulting coefficients and to predict the economic growth of the other half of countries based on their height increases. The scatter plot of the predicted and actual growth rates for one specific random draw is shown in Figure 3, and the countries randomly selected to predict the other half are marked in Table 1. The slope coefficient between actual and predicted is around 1.8 and is significant and R-square is 0.23. This suggests our approach has predictive power out of sample for countries where we lack income data.

Following West (2006) we assess our forecasts $\Delta\hat{y}_{it}$ to the actual data Δy_{it} using the mean squared prediction error (MSPE) as a measure of goodness of fit given by:

$$MSPE = \left[NT^{-1} \sum_{i=1}^{N} \sum_{t=1}^{T} \quad \Delta y_{it} - \Delta\hat{y}_{it} \quad ^2 \right]^{1/2} \tag{23}$$

We also measure the efficiency of the prediction as the slope of the linear regression between the actual outcomes on the prediction. If the efficiency differs from one, we are putting too much – or too little – weight on our predictions and we can improve our prediction by a simple transformation. For comparison purposes we compare our model which produces predictions given by $\Delta\hat{y}_{it}$ with a model where we do not use height data and predict using just country fixed effect and time dummies.

In order to check that our results in Figure 3 are not due to chance and the specific countries selected for estimation, we repeated the out of sample prediction exercise 1,000 times with different random draws of countries in the estimation and prediction samples each time. The results for the MSPE and prediction efficacy are shown in Appendix Table 6. Compared to the baseline model where we do not include height, the models with height have significantly lower MSPE on average compared to the baseline model, though the OLS model performs significantly better than the IV model. The reason for this is clear when we look at the efficiency of the predictions.

The coefficients on the prediction in the linear regression explaining actual outcomes are somewhat less than the one for the baseline and OLS model (columns 1 and 2 in Appendix

Table 6). For the IV model (column 3), however, the efficiency is much lower, 0.356. The IV estimates assume that the actual height changes we see are real and reflect population heights, and they put a large coefficient on these height changes. In fact the measured height changes incorporate a great deal of sampling errors and should have a lower weight as in the OLS estimate. In column 4 of Appendix Table 6, we weigh down the IV prediction by the estimated signal to noise ratio in the cohort height data. This both reduces the MSPE and increases efficiency, which is now much close to one.

Appendix

Appendix–Table 1: Inferring the infant mortality rate from cohort height (Dependent variable: Infant mortality rate per 1,000 live births)

	1	2	3	4	5
	Pooled OLS	Pooled Two Stage Least Squares	Fixed Effects	Country Fixed Effects 5-year Averages	Fixed Effects Two Stage Least Squares
Constant	184.21*** (48.96)	224.70*** (45.81)	578.35*** (59.43)	976.70*** (136.16)	1232.37*** (252.20)
Height	-0.65** (0.31)	-1.08** (0.30)	-2.54*** (0.39)	-5.37*** (0.90)	-7.39*** (1.66)
N	1049	708	1049	234	708
R-squared	0.273	0.234	0.961	0.963	0.951

Notes: Coefficients, standard errors in parentheses, significance level indicated as *(10%), **(5%), ***(1%). Panel data: each observation is for a (country, year). Year dummies added to all models except column 4 in which 5-year dummies were added. In the two stage least squares estimates average cohort height is instrumented with an independent measure of the average height of the same cohort from a previous DHS survey.

Source: Authors calculations based on DHS, World Bank, FAO, PWT data.

Appendix–Table 2: Inferring calorie intake from cohort height (Dependent variable: Calories per person per day)

	1	2	3	4	5
	Pooled OLS	Pooled Two Stage Least Squares	Fixed Effects	Country Fixed Effects 5-year Averages	Fixed Effects Two Stage Least Squares
Constant	-293.87 (398.84)	17.74 (419.76)	-2919.72*** (882.74)	-5960.08** (2298.60)	-7676.56** (3706.91)
Height	15.21*** (2.49)	14.76*** (2.74)	32.07*** (5.91)	52.61*** (15.27)	64.01*** (24.37)
N	1093	736	1093	245	736
R-squared	0.053	0.052	0.760	0.769	0.780

Notes: Coefficients, standard errors in parentheses, significance level indicated as *(10%), **(5%), ***(1%). Panel data: each observation is for a (country, year). Year dummies added to all models except column 4 in which 5-year dummies were added. In the two stage least squares estimates average cohort height is instrumented with an independent measure of the average height of the same cohort from a previous DHS survey.

Source. Authors calculations based on DHS, World Bank, FAO, PWT data.

Appendix–Table 3: Inferring protein intake from cohort height (Dependent variable: Protein grams per person per day)

	1	2	3	4	5
	Pooled OLS	Pooled Two Stage Least Squares	Fixed Effects	Country Fixed Effects 5-year Averages	Fixed Effects Two Stage Least Squares
Constant	-86.04*** (14.29)	-74.83*** (11.80)	-104.15*** (26.16)	-222.70*** (65.74)	-215.41** (97.16)
Height	0.87*** (0.09)	0.85*** (0.08)	0.96*** (0.17)	1.76*** (0.44)	1.70*** (0.64)
N	1093	736	1093	245	736
R-squared	0.088	0.075	0.852	0.860	0.882

Notes: Coefficients, standard errors in parentheses, significance level indicated as *(10%), **(5%), ***(1%). Panel data: each observation is for a (country, year). Year dummies added to all models except column 4 in which 5-year dummies were added. In the two stage least squares estimates average cohort height is instrumented with an independent measure of the average height of the same cohort from a previous DHS survey.

Source: Authors calculations based on DHS, World Bank, FAO, PWT data.

Appendix-Table 4: Inferring life expectancy from cohort height (Dependent variable: Life expectancy in years)

	1	2	3	4	5
	Pooled OLS	Pooled Two Stage Least Squares	Fixed Effects	Country Fixed Effects 5-year Averages	Fixed Effects Two Stage Least Squares
Constant	96.32*** (10.34)	84.13*** (10.32)	-48.03*** (13.90)	-188.81*** (34.94)	-131.58** (45.27)
Height	-0.21*** (0.06)	-0.11 (0.07)	0.70*** (0.09)	1.62*** (0.23)	1.25*** (0.30)
N	1120	756	1120	245	756
R-squared	0.245	0.245	0.941	0.940	0.941

Notes: Coefficients, standard errors in parentheses, significance level indicated as *(10%), **(5%), ***(1%). Panel data: each observation is for a (country, year). Year dummies added to all models except column 4 in which 5-year dummies were added. In the two stage least squares estimates average cohort height is instrumented with an independent measure of the average height of the same cohort from a previous DHS survey.

Source: Authors calculations based on DHS, World Bank, FAO, PWT data.

Appendix–Table 5: Summary of inferring the standard of living from cohort height: Two-stage least squares results with continent dummies (Africa, Asia, Latin America)

Dependent Variable	**Coefficient of height**	**Asia dummy**	**Latin America dummy**	**N**	**R-squared**
Log GDP per capita	0.047*** (0.009)	0.419*** (0.078)	1.461*** (0.078)	773	0.465
Life expectancy (years)	0.623*** (0.09)	5.41*** (0.82)	10.52*** (0.71)	756	0.411
Infant mortality rate (per 1,000)	-4.18*** (0.49)	-27.18*** (4.45)	-39.58*** (3.77)	708	0.325
Calories (calories/day/person)	7.96* (4.28)	-84.00** (37.75)	-55.94 (32.92)	736	0.061
Protein (g/day/person)	0.73*** (0.15)	-1.83 (1.35)	-0.66 (1.18)	736	0.081

Notes: Coefficients, standard errors in parentheses, significance level indicated as *(10%), **(5%), ***(1%). All regressions contain continent dummies and year dummies. Africa dummy has been omitted as it is the base. Height is instrumented with height of the same cohort from a prior survey in the same country.

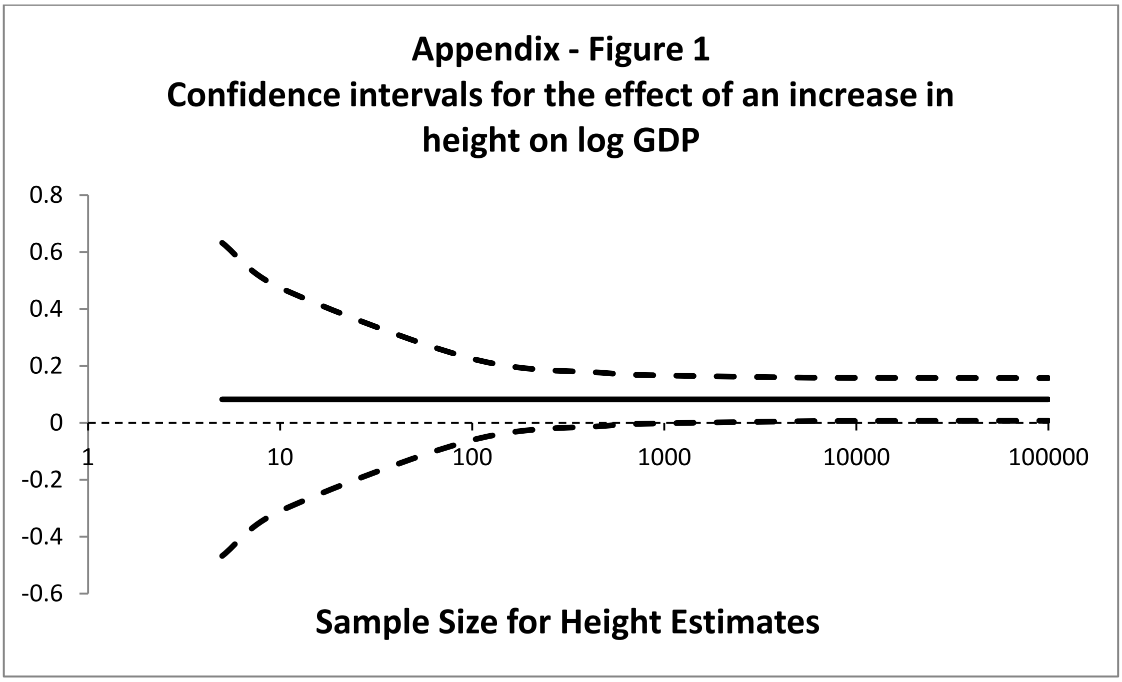
Source: Authors calculations based on DHS, World Bank, FAO, PWT data.

Appendix–Table 6; Goodness of fit of the model in predicting economic growth out of sample

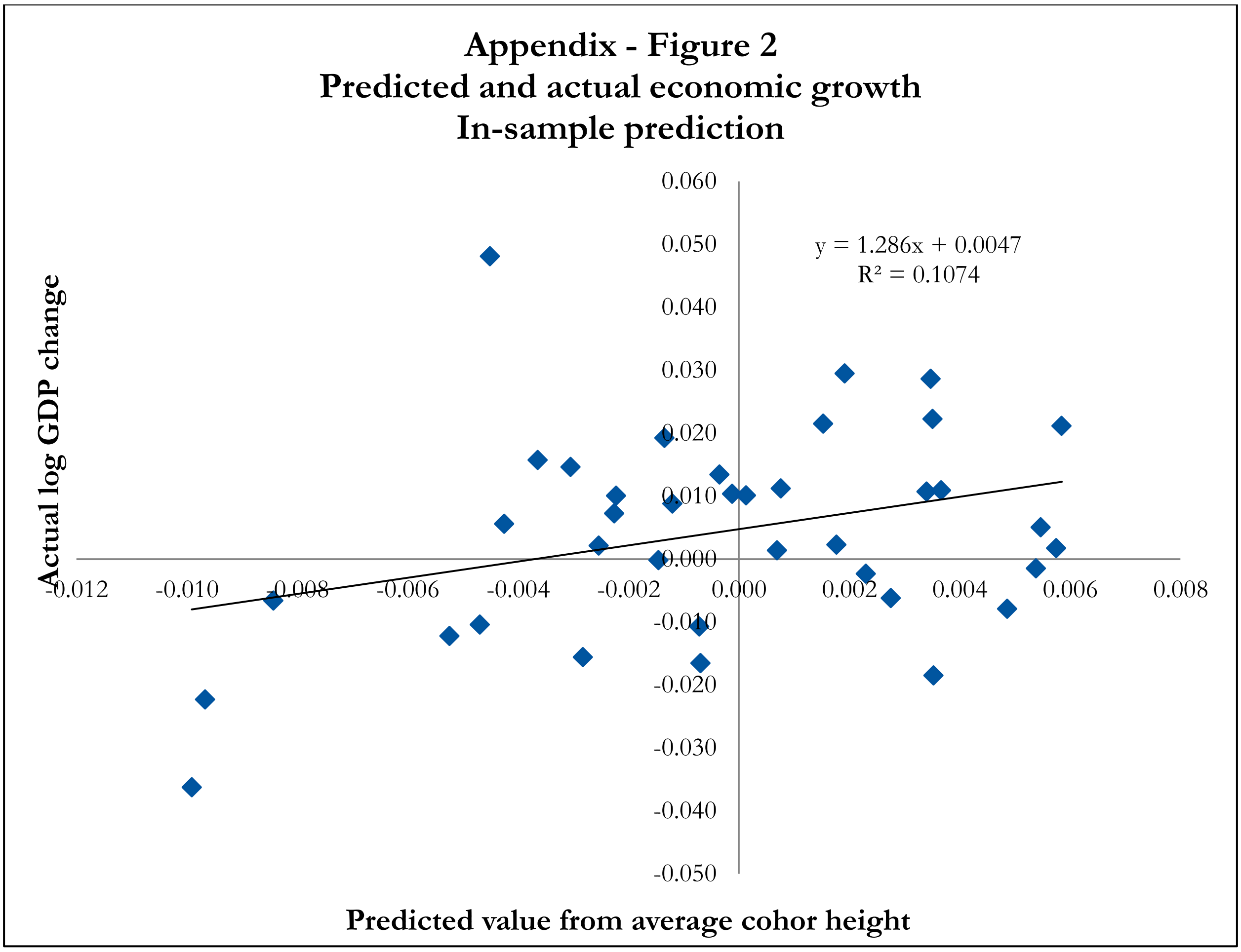
	1	2	3	4
	Baseline model (no height)	OLS Model	IV Model	IV Model Adjusted
Mean Squared Prediction Error	0.201 (0.0001)	0.176 (0.0001)	0.193 (0.0008)	0.178 (0.0001)
Prediction Efficiency	0.754 (0.013)	0.628 (0.011)	0.356 (0.022)	1.157 (0.025)

Notes: Using estimates of half the countries to predict income growth on the other half. Baseline model includes country fixed effects and a time dummies only, OLS and IV models also include height of the cohort born that year in the country. The OLS and IV models are the same as those used to generate the results in columns 3 and 5 of Table 4 respectively. The IV model adjusted reduces the difference between the forecast growth and the mean forecast by the estimated signal to noise ratio in the data. Average outcomes for 1000 replications. Standard errors in parentheses. Prediction efficiency is the coefficient on the prediction when we regress the actual outcome on the prediction.

Source: Authors calculations based on DHS, World Bank, FAO, PWT data.



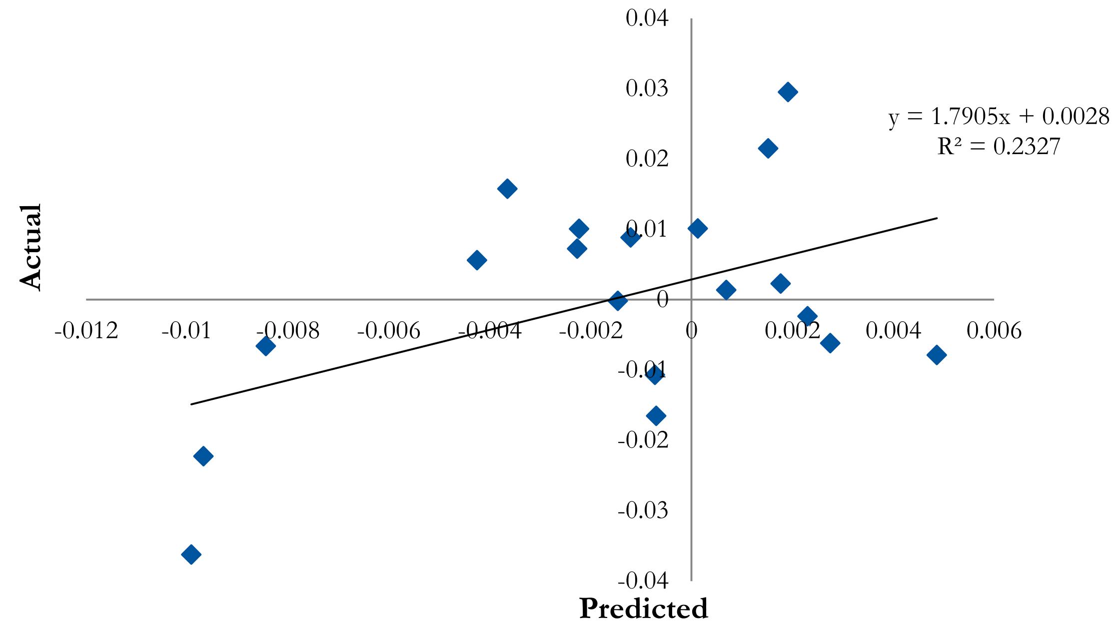
Source: Authors calculations based on DHS, World Bank, FAO, PWT data.



Notes: Predictions for the average rate of economic growth for all 38 countries in our sample based on coefficient estimates from the same sample.

Source: Authors calculations based on DHS, World Bank, FAO, PWT data.

Appendix- Figure 3
Predicted and actual economic growth
Out-of-sample prediction



Notes: Countries that were randomly chosen to estimate the height- income relationship (half the sample) are marked in Table 1. The predictions shown in Figure 3 are for the remaining 19 unmarked countries. This is an example of one of the 1000 replicates used to generate the results in Appendix Table 6.

Source: Authors calculations based on DHS, World Bank, FAO, PWT data.