Inequality, Human Capital and Development: Making the Theory Face the Facts*

Chris Papageorgiou[†] Nor Azam Abdul Razak[‡]

January 19, 2010

Abstract

In their seminal contribution Galor and Zeira (1993) show that income inequality can have a major effect on economic development and prompted a vast literature investigating alternative channels and mechanism through which the inequality-development relationship may work. In this paper we test one of such channels, namely the inequality-human capital-development hypothesis. Using a sample of 46 countries for the period 1970–2000 we obtain results that lend strong support to this relationship. Our baseline results are shown to be unaffected from several robustness checks.

Keywords: Income inequality, human capital, development
JEL Classification: O11, O15, O40

*We are grateful to the editor and one referee for insightful comments. Special thanks go to Oded Galor for his extremely valuable suggestions on an earlier version of the paper. For helpful discussions we also thank Oya Celasun, Areendam Chanda, Daniel Chen, Oded Galor, Carter Hill, Doug McMillin, Chris Parmeter, Nicola Spatafora, Antonio Spilimbergo, Joseph Zeira, and participants in many universities and conferences at which this paper has been presented. The views expressed in this study are the sole responsibility of the authors and should not be attributed to the International Monetary Fund, its Executive Board, or its management.

[†]Corresponding author: Research Department, International Monetary Fund, 700 19th Street, N.W. Washington, DC 20431, email: cpapageorgiou@imf.org, tel: (202) 623-7503, fax: (202) 589-7503.

[‡]Department of Economics, College of Arts and Sciences, Northern University of Malaysia, email: azam@uum.edu.my.

1 Introduction

In their pioneering work, Galor and Zeira (1993; GZ thereafter) proposed a theory in which income inequality was shown to have severe and detrimental effect on economic development. The theory was powerful as it countered the representative agent model, suggesting that heterogeneity is critical for the understanding of macroeconomic behavior. Building on GZ an entire literature emerged in which several channels and associated mechanisms have been considered through which the inequality-development relationship may work.

Although, the theoretical underpinnings of this relationship have been extensively studied and several mechanisms in which human capital is influenced by income inequality have been revealed, there has been less effort in the empirical literature to take these theories to the data.[1] This paper contributes to filling this gap by conducting a systematic analysis of the inequality-human capital-development hypothesis in a sample of 46 countries for the period 1970–2000.

More specifically, GZ advance the following hypotheses:

1. Inequality has a negative effect of on economic development (in all but the very poor economies).
2. Inequality has an adverse effect on human capital formation
3. In addition it proposes a specific mechanism for this effect; namely the credit market imperfection mechanism).

While the main contribution of GZ is being the first that propose that inequality in fact has an adverse effect on economic development, the second contribution is in identifying the human capital channel. In the context of the modeling of this channel, GZ highlighted the credit market imperfection mechanism, while other contributions in the literature have focused on competing mechanisms.[2]

In this paper we provide evidence for the hypotheses (1) and (2) above. We have also attempted to test alternative mechanisms within the human capital channel, including credit market imperfection and differential fertility, but without success because of severe data limitations.

Our results provide strong support for the inequality-human capital-development hypothesis. In an exhaustive robustness analysis, we show that these baseline results are robust across different

[1] The empirical literature includes Alesina and Rodrik (1994), Persson and Tabellini (1994), Alesina and Perotti (1996), Clarke (1995), Deininger and Squire (1998), Forbes (2000), Barro (2000), Sylwester (2000), and Durlauf, Johnson and Temple (2005).

[2] See Galor (forthcoming) for a summary of these papers.

model specifications, estimation methods, and additional control variables. Although we have attempted to test for the credit constraint and fertility differential mechanisms of the relationship, we were not successful to go far because of severe data limitations.

The rest of the paper is organized as follows. Section 2 provides a brief theoretical motivation for the empirical analysis. Section 3 specifies the regression equations used in estimation, while Section 4 takes a look at the datasets employed in the regression analysis. Section 5 presents and discusses our baseline results and several robustness checks. Section 6 concludes.

2 Theoretical Motivation

We begin our analysis by providing a sketch of the pioneer paper by Galor and Zeira (1993). GZ introduced an overlapping-generation model of the economy with altruism, where the economy consists of individuals who live for two periods. During the first period, these individuals may choose to work or invest in human capital; during the second period, they simply work. If they invested in human capital during the first period, they would work as skilled workers in the second period and receive high wages; otherwise, they would work as unskilled workers in both periods and receive low wages. The work-study decision in the first period depends partly on the amount of wealth they inherit from their parents. Assuming that this inheritance varies from one person to another, then those with greater inheritance stand a better chance of acquiring education. If one's inheritance is not sufficient, then one can still invest in human capital by borrowing. However, due to assumed imperfect credit markets, some individuals are credit-constrained. That is, there are individuals who cannot afford to acquire education because their inheritance falls short of a certain minimum amount, and they are denied educational loans.

[Insert Figure 1 about here]

Under the Galor-Zeira model, population is gradually partitioned into two groups separated by an unstable equilibrium point, denoted by point g in Figure 1. That is, those individuals who receive inheritance less than g will end up in the poor group, x_{poor}, and those who receive inheritance more than g will end up in the rich group, x_{rich}, in the long-run. The reason for this dynamic evolution is that a minimum amount of inheritance is needed before subsequent generations can provide enough bequests for their offspring as well.

It can be inferred from Figure 1 that the long-run levels of income are positively related to the initial number of individuals who inherit more than g. To illustrate, consider an economy characterized by three different scenarios. First, one-half of the population is concentrated around f and the remaining one-half around h. Second, one-third of the population is concentrated around f and the remaining two-third around h. Third, two-thirds of the population is concentrated around f and the remaining one-third around h. In all cases, the fraction of population that lives around f will move to x_{poor} and the fraction of population that lives around h will move to x_{rich}.

With reasonable values of income at x_{poor}; f; g; h; and x_{rich}, we can deduce the following: income tends to remain unchanged in the first scenario, rise in the second scenario, and fall in the third scenario. Thus, the larger the fraction of people who inherit more than g, the higher the long-run income tends to be. If we let g be the threshold that separates a poor from a non-poor economy, then we obtain the following conclusions: 1) An initially poor economy will end up poor in the long run, 2) An initially non-poor economy with wealth distributed among many will end up rich, and 3) An initially non-poor economy with wealth distributed among few will end up poor.

GZ gave way to an entirely new theoretical literature trying to uncover the channels and mechanisms under which inequality influenced the process of economic development; see e.g. the mobility channel (Galor and Tsiddon, 1997), the fertility channel (Galor and Weil, 1996; Galor and Zang, 1997; Dahan and Tsiddon, 1997; Croix and Doepke, 2003), political economy, political instability and land inequality (Galor, Moav and Vollrath, 2009).

3 Model Specification

In this section, we specify the regression equations that will form the basis of our empirical analysis. Although, as discussed above, several strands in this literature may differ in their underlying mechanisms through which income inequality compromises human capital, all proposed models imply the following reduced-form relationship first pioneered by GZ:

$$Income\ Inequality => Human\ Capital => Growth \tag{1}$$

We estimate this relationship using two equations: In the first equation, income is a function of education and other explanatory variables in the Solow growth regression. In the second equation, education is a function of income inequality and a dummy variable for poor countries. We introduce a dummy variable for poor countries since the implications of both models are not applicable to an initially poor country. In particular, we estimate the following two-stage specification:

$$Income = \alpha_1 + \alpha_2.Educ + \alpha_3.Invest + \alpha_4.(n + g + \delta) + u, \tag{2}$$

$$Educ = \beta_1 + \beta_2.Gini + \beta_3.Poor + v, \tag{3}$$

where *Income* is the level of long-run income per capita, *Educ* is defined as the ratio of skilled to unskilled labor or the average human capital investment, *Invest* is the amount of physical capital Investment, $(n + g + \delta)$ is the sum of the rates of population growth (n), technological progress (g), and capital depreciation (δ), *Gini* is the *Gini* index which measures the degree of inequality, *Poor* is a dummy variable equal to one for an initially poor country and zero otherwise, and u and v are the error terms. A priori, we expect the coefficients of *Gini*, *Poor*, and $(n + g + \delta)$ to be negative and those of *Educ* and *Invest* to be positive.

3.1 Alternative specifications

We conclude our discussion on the choice of estimation specifications, by comparing our specifications with those found in the existing literature. First, let us compare our regression specifications with two closely related ones; namely, those of Perotti (1996) and Sylwester (2000). Perotti (1996) employed the following structural model:

$$Growth = \alpha_1 + \alpha_2.Educf + x'\gamma + u,$$

$$Educf = \beta_1 + \beta_2.Mid + \beta_3.Educ_{fem} + \beta_3.Educ_{male} + v,$$

where *Growth* is the growth rate of per capita income for the period 1960−1985, *Educf* is the flow of human capital, **x** is a vector of control variables (which includes initial income per capita and PPP investment deflator), *Mid* is the income share of the third and fourth quintiles of population which measures income equality (as opposed to income inequality), *Educfem* is the stock of female human capital, and *Educmale* is the stock of male human capital. There are a few notable differences between Perotti's and our structural model.

First, Perotti's dependent variable in the first equation is *Growth* while ours is *Income*. We use *Income* because that is what is implied by the Galor-Zeira model; Perotti used *Growth* because that is a standard practice in the growth empirics. This should not be a problem, however, because we can always transform our level regression into the growth regression. Second, he discriminated between two measures of human capital stock and flow, and he treats the flow measure as endogenous and the stock measure as exogenous. Third, he included a PPP Investment deflator in order to account for market distortion. However, this variable is not an important determinant of growth. Finally, Perotti did not include *Invest* and *Poor* variables. The omission of the former follows from his reduced-form model which tries to accommodate other theoretical models. Nevertheless, this variable is an important determinant of growth.

Sylwester (2000) employed the following structural model:

$$Growth = \alpha_1 + \alpha_2.Educ\$ + x'\gamma + u,$$

$$Educ\$ = \beta_1 + \beta_2.Gini + \beta_3.Dem + \beta_3.n + v,$$

where *Educ$* is the amount of educational expenditures, $\mathbf{x}$ is a vector of control variables (which includes the lagged value of *Educ$*, the stock of human capital, and initial income per capita), *Dem* is a dummy variable equal to one for a democratic country and zero otherwise, and n is the growth rate of population; other variables are as defined before.

To begin with, Sylwester (2000) did not base his specification on a theoretical model. His main concern is to determine whether income inequality affects growth through education. It turns out that his specification is consistent with the credit constraint model. There are several differences, though. First, Sylwester used a distinctive measure of human capital, namely, educational expenditures. This measure can be thought of as another proxy for the flow of human capital. Second, he employs both the stock and flow of human capital. Third, he also included the lagged value of educational expenditures in both of his equations. Finally, he added *Dem*, a variable which is implied by the political-economy model but not by the GZ model.

In addition, there exists a notable complementary literature on the link between human-capital inequality and growth; see e.g. Castello-Climent and Domenech (2002, 2008, 2009). While these papers do not focus on the two mechanisms explored here, they are clearly relevant to this work as they consider alternative definitions to inequality, and alternative ways in which human capital affects growth.

4 Data

We proceed by collecting the cross-country data for all of the variables identified in those equations from various sources. It turns out that the *Gini* data impose substantial restrictions on the number of available observations. If we wish to use these data for as early as 1960, then we end up with as few as 14 observations. The number of available observations rises as we adjust the beginning period upward: 27 if we begin from 1965, 41 if 1970, 52 if 1975, and 62 if 1980.

To have as many observations as possible while having data for a relatively long period of time, we relax the time classification for the inequality data. That is, data that range between 1960 and

1965 are treated as the 1960 data, data that range between 1970 and 1975 are treated as the 1970 data, and data that range between 1980 and 1985 are treated as the 1980 data. With this slight relaxation of classification, we have the following: 75 observations if we begin from 1980, 56 if 1970, 29 if 1960, etc. We settle for data that begin from 1970; hence, we have 56 observations. When we match these data with the data on other variables, we lose another 10 observations. Thus, we end up with 46 observations.

Given this restriction, we collect the necessary data for 46 countries during the period 1970−2000 as follows:

1. *Gini*: This variable, which measures the degree of income inequality, is defined as the log of the *Gini* index in 1970 or its closest neighboring period but cannot exceed 1975. *Gini* is taken from Deininger and Squire (1996), who make the necessary efforts to compile high-quality income distribution data. In particular, they impose three stringent quality criteria before the data can be accepted. First, data must be based on household surveys (not from national accounts that make some assumptions about patterns of income inequality). Second, data must be based on comprehensive coverage of population (not based on some segments of population only). Third, data must be based on comprehensive coverage of income sources (not based on wage incomes only but also nonwage incomes).

2. *Income*: The log of the real GDP per capita in 2000. The source is Penn World Table version 6.1 (RGDPCH series).

3. *Educ*: The log of the ratio of the amount of skilled labor to unskilled labor during the period 1970−2000. The amount of skilled labor is defined as the percentage of the population who has attained certain level of education multiplied by the quantity of labor. The data on the percentage of population with certain education level are taken from Barro and Lee (2001) while the data on labor force are taken from PWT6.1. Appendix A discusses further details on this variable. In the robustness analysis, we also use the alternative definition of the log of average years of schooling for population over 25 years old during the period 1970−2000. This measure is taken from Barro and Lee (2001).

4. Invest: The log of the annual average of the ratio of real Investment to GDP during the period 1970−2000. The data for this variable are taken from PWT6.1.

5. $(n + g + \delta)$: The log of the sum of the rates of population growth (n), technological progress

(g), and capital depreciation (δ). The population growth rate data (n), taken from PWT6.1, is defined as the annual average of the population growth rate during the period 1970−2000. We follow the literature by setting g + $\delta = 0.05$.

6. *Poor*: This variable is defined as a dummy variable, which is equal to 1 for any countries that are classified by the World Bank as low-income countries in 1970 (and 0 otherwise) based on their income range. Since the data for 1970 are not available, we use the data for 1972. These data are taken from the World Tables 1976, published by the World Bank.

5 Results

Employing cross-country data for 46 countries during the period 1970−2000, we conduct an empirical analysis to test the relationship in equation (1) using equations (2) and (3). In particular, we estimate equation (2) by the instrumental variable (IV) method, where *Educ* is instrumented by *Gini* and *Poor*. Hence, equation (3) corresponds to the first-stage regression and equation (2) the second-stage regression.[3,4]

As mentioned earlier, *Educ* is defined as (the log of) the ratio of skilled to unskilled labor. However, it remains to specify what constitutes skilled and unskilled labor. According to Duffy, Papageorgiou, and Perez-Sebastian (2004), however, six measures of skilled labor could be constructed: a) workers who have completed tertiary education (L_{s0}), b) workers who have attained some tertiary education (L_{s1}), and so on (see Appendix A for details). Of these six, the first two are probably more plausible than the others because the ability to think and learn complex concepts (such as learning a new computer language) is probably more associated with the ability to pursue college education. Of the two, the latter is preferred because skilled labor might plausibly encompass those who have moved beyond secondary education. Accordingly, we employ (L_{s1}/L_{u1}) as the benchmark measure of *Educ* in our analysis.

We begin by running the first-stage regression corresponding to equation (2) and present the estimation results in Table 1. Column (1a) shows that the coefficients of *Gini* and *Poor* are individ-

[3] The empirical literature on the inequality-growth relationship usually adds three regional dummy variables (the Latin American countries, the Asian countries, and the African countries) in order to control for institutional and cultural factors that might differ across regions. Since there are only two African countries in our 46-country sample, we add two regional dummies only, Latin and Asia, to our second-stage regression.

[4] Since Invest, (n + g + δ), Latin, and Asia are assumed to be exogenous, their coefficients will enter the first-stage regression as well to ensure that Educ is estimated with the optimal set of instruments [see Chapter 5 of Wooldridge (2002)]. However, these exogenous variables have little meaning in the first-stage regression. Hence, their coefficients will be suppressed from the first-stage regression results.

ually significant at the 1% level. Since both coefficients are also jointly significant at the 5% level, we proceed with the second-stage regression and present the results in Column (1b).[5] We observe that the coefficients of L_{s1}/L_{u1}, *Invest*, and $(n + g + \delta)$ enter with the expected signs and are individually significant at least at the 5% level. However, the coefficients of regional dummies are individually insignificant even at the 10% level. Since the coefficients of key variables (*Gini*, *Poor*, and L_{s1}/L_{u1}) enter with the correct signs and are significant, we take these results as evidence in favor of the inequality-human capital-income hypothesis.

The fact that our dependent variable, *Income*, is measured in the year 2000, while some of our explanatory variables (*Invest* and n)[6] are measured as averages over the period 1970−2000 may make our estimation results susceptible to simultaneity bias (i.e., the direction of causality may run from these variables to *Income* instead). In the growth empirics, this endogeneity issue is partly taken care of by instrumenting the relevant regressors (*Invest* and n in our context) with their lagged values [see Barro and Sala-i-Martin (2004)].

Before we do that, however, we test the endogeneity of *Invest* and n using the Hausman test. First, we estimate the second-stage regression with and without instrumenting *Invest* and n with their respective lagged values, which are measured as averages over the period 1965−1995. Second, we test whether the difference between estimates obtained from the regression with and without instrumenting *Invest* and n is statistically significant. (Note that L_{s1}/L_{u1} is always instrumented by *Gini* and *Poor* by the theoretical implication.) Unfortunately, the Hausman test fails to deliver any results because the test statistic is negative. To get around this problem, we adopt the auxiliary regression version of the Hausman test.[7] In this case, we find evidence that L_{s1}/L_{u1}, *Invest*, and n are endogenous.

Given the above results, we repeat our baseline estimation by instrumenting *Invest* and n with their respective lagged values. As reported in Columns (2a) and (2b), we find that, except for the regional dummies, the coefficients of all variables enter with the anticipated signs and are individually significant at mostly the 5% level. Compared to the corresponding coefficients in Columns (1a) and (1b), we see that the results are fairly robust (the only sensitive coefficient is

[5]The second-stage regression is conducted only if Gini and Poor are jointly significant.

[6]Although L_{s1}/L_{u1} data is also an average of the period 1970 − 2000, this should not pose any simultaneity problem because it is instrumented by Gini and Poor.

[7]This method can be summarized in the following steps [see Chapter 15 of Wooldridge (2006)]: First, we run the first-stage regression for each Ls1/Lu1, Invest, and (n + g + δ). Second, we extract residuals obtained from each first-stage regression. Third, we run the second-stage regression with the inclusion of these residuals using the method of ordinary least squares (OLS). Finally, we test whether the estimated coefficients from the residuals are jointly significant; if they are, then L_{s1}/L_{u1}, Invest, and (n + g + δ) are deemed endogenous.

that of *Poor*).

One may argue that our baseline results might be subject to sample selection bias since they are based on an exceedingly small sample size, 46. This problem arises because the data on *Gini* is not available for many countries in early years. One way to increase the sample size would be to curtail the sample period to 1980−2000. However, doing so will increase the sample size only marginally; the sample size becomes 61 instead of 46. Another way to increase the sample size would be to work with panel data (as opposed to cross-sectional data). So we construct a panel data of countries with a five-year interval during 1970−2000, where *Gini* and *Poor* are measured at 1970, 1975, . . . , 1995, L_{s1}/L_{u1}, *Invest* and $(n + g + \delta)$ are measured as averages of 1971−1975, 1976−1980, . . . , 1996−2000, and *Income* is measured at 1975, 1980, . . . , 2000. Including only those data for which there are at least two consecutive observations, we end up with an unbalanced panel of 53 countries and 226 observations.

With this expanded sample size, we re-estimate our model by the pooled IV method. As before, we start with the first-stage regression with regional dummies. As shown in Columns (3a) and (3b), the coefficients of all variables enter with the correct signs and are individually significant mostly at the 1% level. It is worth noting that, with the enlarged sample size, the coefficients of regional dummies are also individually significant at least at the 5% level. Compared to the corresponding coefficients in Columns (1a) and (1b), we see that there is a remarkable change in the magnitude of *Gini*, *Poor*, and $(n + g + \delta)$. Nonetheless, since the results on key variables remain intact, they lend further support for the inequality-human capital-income hypothesis.

[Insert Table 1 about here]

Robustness

We have been using the ratio of skilled to unskilled labor as the closest proxy for human capital investment in GZ. In the growth empirics, however, the usual proxy for human capital investment is school attainment rate. In order to see whether our estimation results are sensitive to a change in the education proxy, we repeat our previous exercises with this alternative proxy. In particular, we employ a measure of school attainment rate, *AvgEduc*, in lieu of L_{s1}/L_{u1}.[8]

We re-estimate our reduced-form specification and present the results in Table 2. In Columns (1a) and (1b), the most basic reduced-form specification, we see that the coefficients of key variables and that of *Invest* continue to enter with the correct signs and are significant at the 1% level. Unlike

[8] *AvgEduc* is defined as (the log of) average years of schooling for population over 25 years old during the period 1970 − 2000, the data of which are taken from Barro and Lee (2001).

the corresponding specification in Table 1, however, the coefficient of $(n + g + \delta)$ enters with the wrong sign and is insignificant, and those of regional dummies are significant. In Columns (2a) and (2b), a reduced-form specification with instrumented *Invest* and n, we observe that the coefficients of key variables and that of *Invest* continue to enter with the expected signs and are significant at least at the 5% level. In contrast to the corresponding specification in Table 1, however, the coefficient of $(n + g + \delta)$ is insignificant, and those of regional dummies are significant. Finally, we find that similar results continue to hold in the reduced-form specification with panel data; see Columns (3a) and (3b).

[Insert Table 2 about here]

Thus far, we have defined skilled labor as those individuals who have attained at least some tertiary education (L_{s1}). It may be argued that our baseline results could be sensitive to alternative definitions. To entertain this possibility, we redefine skilled labor as those who have completed tertiary education (L_{s0}). Consequently, we employ L_{s0}/L_{u0} in lieu of L_{s1}/L_{u1}. With this slight change, we re-estimate our reduced-form specification and present the results in Table 3. In Columns (1a) and (1b), we see that the baseline results remain intact with respect to the sign, magnitude, and significance of the coefficients of all variables.[9]

All of these results notwithstanding, Duffy, Papageorgiou and Perez-Sebastian (2004) point out that the way skilled and unskilled labor are defined suffers from an aggregation problem. For example, the (L_{s1}/L_{u1}) data that we use treat workers with different levels of education equally. If labor is paid according to its marginal revenue product, then workers with a higher level of education should be given a greater weight than workers with a lower level of education. To overcome this aggregation problem, we follow these researchers in weighting the (L_{s1}/L_{u1}) data according to the marginal revenue product of labor. Unfortunately, the weighting procedure requires some additional data on the return to education and on the duration of education at various levels. It turns out that data on the return to schooling are not available for many countries; this results in the reduction of our sample size to 32. Therefore, we opt to work with the panel data. Utilizing the same panel data set as before (but interacting it with data on the return to education and the duration of education) yields an unbalanced panel of 32 countries and 145 observations.

Using the weighted (L_{s1}/L_{u1}) data, we re-estimate our model by the pooled IV method. In the first-stage regression, the results of which are documented in Column (3a), we find that, al-

[9] Table B1 in Appendix B shows that, even with further modifications of the skilled labor definition, we continue to obtain similar results.

though the coefficients of *Gini* and *Poor* enter with the expected signs, the coefficient of *Gini* is insignificant.[10] One way to interpret these unfavorable results is that the hypothesis is rejected when it is confronted with better (weighted) human capital data. However, it could also be argued that these poor results are driven by a reduction in the sample size from 226 to 145. To test for this equally plausible interpretation, we re-estimate this specification using the unweighted (L_{s1}/L_{u1}) data with 145 observations. Instead, the results of the first-stage regression in Column (4a) appear to mimic the results in Column (3a); i.e. although the coefficients of *Gini* and *Poor* enter with the expected signs, the coefficient of *Gini* is insignificant suggesting that our results are sensitive to changes in the sample size.[11]

[Insert Table 3 about here]

6 Conclusion

In this paper, we conducted an empirical analysis to test two of the key implications of the Galor and Zeira (1993) model based on a cross-section data of 46 countries during the period 1970–2000. Specifically we tested the basic income inequality-development hypothesis and further the particular human capital channel through which this relationship may work. We have shown strong evidence in favor of both hypotheses under our baseline and robustness estimations.

There are two main issues that could cast doubt on our findings: small sample size and simultaneity. On the first issue, we repeated our analysis with a five-year panel data of those countries during the same period. With an enlarged sample size of 226 observations, our cross-section results continued to hold. On the second issue, we repeated our analysis by instrumenting the explanatory variables with their lagged values. In this case too, we continued to obtain results consistent with our baseline results. In addition, we complemented our baseline estimation with a series of robustness checks.

[10] In addition, both coefficients are also found to be jointly insignificant, thereby precluding us from conducting the second-stage regression.

[11] We have attempted to also test the separate mechanisms financial constraints vs. fertility differntials. Our efforts to go further and separate the potential mechanisms were severely compromised due to data limitations. To test the two mechanisms we used two additional datasets:

PrivCredit: Private credit by deposit money banks and other financial institutions to GDP. The source of these data is Beck, Demirgüç-Kunt and Levine (2000).

Fertd: The fitted value of the overall fertility obtained from regressing the overall fertility variable on average years of education; therefore, Fertd measures the variation in the overall fertility that is explained by educational attainment. The source of the Fertd data is Barro and Lee (1994).

When merging these datasets with the original ones we could only use around 30 observations which did allow us to credibly perform our estimation.

Nevertheless, we acknowledge some further limitations of our study. First, our findings are based on a cross-country sample which suffers from well-documented measurement error. On top of that our inequality dataset excludes most African countries and our results may be driven by this omission. Second, although we have tried to correct for endogeneity problems as best as we could, we can claim that our attempts only partly address these problems. Third, although we have attempted to test alternative mechanisms within the human capital channel, data limitations did not allow us to produce credible results. As more detailed data become available testing for the competing mechanisms will be a promising line of research.

References

Alesina, A. and R. Perotti (1996), "Income Distribution, Political Instability, and Investment," *European Economic Review*, 40: 1203−1228.

Alesina, A. and R. Rodrik (1994), "Distributive Politics and Economic Growth," *Quarterly Journal of Economics*, 109: 465−490.

Barro, R. (2000), "Inequality, Growth, and Investment," *Journal of Economic Growth*, 5: 5−32.

Barro, R. and J.-W. Lee (1994), "Data Set for a Panel of 138 Countries," *Mimeo*: Harvard University, Cambridge, MA.

Barro, R. and J.-W. Lee (2001), "International Data on Educational Attainment: Updates and Implications," *Oxford Economic Papers*, 53: 541−563.

Barro, R. and X. Sala-i-Martin (2004), *Economic Growth*, 2nd Edition, Cambridge: MIT Press.

Caselli, F. and W.J. Coleman (2006), "The World Technology Frontier," *American Economic Review*, 96: 499−522.

Clarke, G. (1995), "More Evidence on Income Distribution and Growth," *Journal of Development Economics*, 47: 403−427.

Castello-Climent, A. and R. Domenech (2004), "A Reassessment of the Relationship between Inequality and Growth: What Human Capital Inequality Data Say?," Working Papers. Series EC 2004-15, Instituto Valenciano de Investigaciones Económicas, S.A. (Ivie).

Castello-Climent, A. and R. Domenech (2002), "Human Capital Inequality and Economic Growth: Some New Evidence," *Economic Journal*, 112: C187−C200.

Castello-Climent, A. and R. Domenech (2008), "Human Capital Inequality, Life Expectancy and Economic Growth," *Economic Journal*, 118: 653−677.

Dahan, M. and D. Tsiddon (1998), "Demographic Transition, Income Distribution, and Economic Growth," *Journal of Economic Growth*, 3: 29−52.

Deininger, K. and L. Squire (1996), "A New Dataset Measuring Income Inequality," *World Bank Economic Review*, 10: 565−591.

Deininger, K. and L. Squire (1998), "New Ways of Looking at Old Issues: Inequality and Growth," *Journal of Development Economics*, 57: 259−287.

de la Croix, D. and M. Doepke (2003), "Inequality and Growth: Why Differential Fertility Matters," *American Economic Review*, 93: 1091−1113.

Duffy, J., C. Papageorgiou, and F. Perez-Sebastian (2004), "Capital-Skill Complentarity? Evidence from a Panel of Countries," *Review of Economics and Statistics*, 86: 327−344.

Durlauf, S., P. Johnson, and J. Temple (2005), “Growth Econometrics,” In: Aghion, P. and S. Durlauf (eds.), *Handbook of Economic Growth*, 1A: 555−677.

Forbes, K. (2000), “A Reassessment of the Relationship between Inequality and Growth,” *American Economic Review*, 90: 869−887.

Galor, O. (forthcoming), *Inequality and Economic Development: The Modern Perspective*.

Galor, O., O. Moav, and D. Vollrath (2009), “Inequality in Land ownership, the Emergence of Human Capital Promoting Institutions and the Great Divergence,” *Review of Economic Studies*, 76: 143-179.

Galor, O. and D. Tsiddon (1997), “Technological Progress, Mobility, and Economic Growth,” *American Economic Review*, 87: 363−382.

Galor, O. and D. Weil (1996). “The Gender Gap, Fertility, and Growth,” *American Economic Review*, 86: 374−387.

Galor, O. and J. Zeira (1993), “Income Distribution and Macroeconomics,” *Review of Economic Studies*, 60: 35−52.

Galor, O. and H. Zang (1997), “Fertility, Income Distribution, and Economic Growth: Theory and Cross-Country Evidence,” J*apan and the World Economy*, 9: 197−229.

Li, H. & H. Zou (1998), “Inequality is not Harmful for Growth: Theory and Evidence,” *Review of Development Economics*, 2: 318−334.

Lucas, R.E. (1988), ”On the Mechanics of Economic Development,” *Journal of Monetary Economics*, 22: 3−42.

Moav, O. (2005), ”Cheap Children and Persistence of Poverty,” *Economic Journal*, 115: 88−110.

Penn World Tables, version 6.1. *http://pwt.econ.upenn.edu/php_site/pwt61_form.php*

Perotti, R. (1996), ”Growth, Income Distribution, and Democracy: What the Data Say,” *Journal of Economic Growth*, 1: 149−187.

Persson, T. and Tabellini, G. (1994), ”Is Inequality Harmful for Growth?” *American Economic Review*, 84: 600−621.

Sylwester, K. (2000), ”Income Inequality, Educational Expenditures, and Growth,” *Journal of Development Economics*, 63: 379−398.

Wooldridge, J. (2002), *Econometric Analysis of Cross Section and Panel Data*, Cambridge, MA: MIT Press.

Wooldridge, J. (2006), *Introductory Econometrics: A Modern Approach*, 3rd Edition, Thomson South-Western.

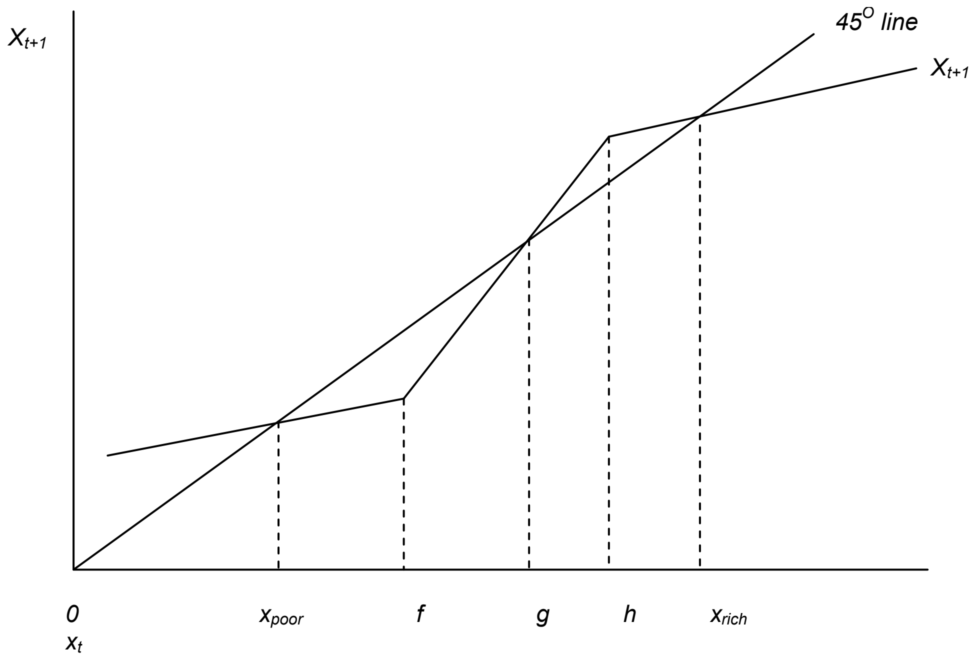

Figure 1: The Dynamics of Galor-Zeira Model

Table 1. Reduced Form Estimation: Baseline Results
[$Educ = L_{s1}/L_{u1}$; Sample Period: 1970–2000]

Dependent Variable	L_{s1}/L_{u1} (1a) 2SLS 1st stage	*Income* (1b) 2SLS 2nd stage	L_{s1}/L_{u1} (2a) 2SLS-inst. 1st stage	*Income* (2b) 2SLS-inst. 2nd stage	L_{s1}/L_{u1} (3a) Panel 1st stage	*Income* (3b) Panel 2nd stage
Constant	13.578*** (2.88)	3.644* (1.73)	12.302** (2.68)	1.930 (0.86)	1.612 (0.61)	5.703*** (5.64)
Gini	−2.624*** (−4.27)		−2.445*** (−4.17)		−1.465*** (−3.83)	
Poor	−1.723*** (−3.99)		−0.915* (−1.92)		−1.120*** (−4.71)	
L_{s1}/L_{u1}		0.669*** (5.01)		0.430** (2.33)		0.503*** (6.44)
Invest		0.409** (2.37)		0.891** (2.72)		0.758*** (5.73)
$(n + g + \delta)$		−2.198*** (−2.99)		−2.139** (−2.65)		−0.878*** (−2.73)
Latin		−0.134 (−0.60)		−0.240 (−0.97)		−0.239** (−2.23)
Asia		0.101 (0.40)		−0.151 (−0.49)		−0.421*** (−4.12)
Adj. R^2	0.51	0.71	0.57	0.68	0.42	0.77
Obs.	46	46	46	46	226	226

Notes: *Educ* is defined as the ratio of skilled to unskilled workers, L_{s1}/L_{u1}, as defined in the main text. Except for dummies, all variables are expressed in logs. Estimation is done by 2SLS; columns (1a) and (1b) report results from the first- and second-stage regressions, respectively; columns (2a) and (2b) report results from the first- and second-stage regressions with instrumented *Invest* and $(n + g + \delta)$; columns (3a) and (3b) report results from the first- and second-stage panel regressions. t-values are in parentheses; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 2. Reduced Form Estimation: Robustness Results
[*Educ* = *AvgEduc*; Sample Period: 1970−2000]

Dependent Variable	*AvgEduc* (1a) 2SLS 1st stage	*Income* (1b) 2SLS 2nd stage	*AvgEduc* (2a) 2SLS-inst. 1st stage	*Income* (2b) 2SLS-inst. 2nd stage	*AvgEduc* (3a) Panel 1st stage	*Income* (3b) Panel 2nd stage
Constant	2.706 (1.26)	7.750*** (3.39)	1.981 (0.92)	5.143* (1.97)	0.558 (0.49)	5.880*** (5.31)
Gini	−0.999*** (−3.57)		−0. 923*** (−3.35)		−0.658*** (−4.04)	
Poor	−0.846*** (−4.30)		−0. 588** (−2.62)		−0.428*** (−4.22)	
AvgEduc		1.610*** (5.64)		1.137*** (2.84)		1.147*** (5.12)
Invest		0.337** (2.04)		0.795** (2.58)		0.815*** (6.72)
$(n + g + \delta)$		0.726 (0.81)		−0.041 (−0.04)		0.393 (0.89)
Latin		−0.591*** (−2.95)		−0. 546** (−2.65)		−0.303*** (−3.39)
Asia		−0.370* (−1.75)		−0.451* (−1.98)		−0.632*** (−7.46)
Adj. R^2	0.63	0.75	0.65	0.73	0.54	0.78
Obs.	46	46	46	46	226	226

Notes: *Educ* is defined as the average years of education, as defined in the main text. Except for dummies, all variables are expressed in logs. Estimation is done by 2SLS; columns (1a) and (1b) report results from the first- and second-stage regressions, respectively; columns (2a) and (2b) report results from the first- and second-stage regressions with instrumented *Invest* and $(n + g + \delta)$; columns (3a) and (3b) report results from the first- and second-stage panel regressions. t-values are in parentheses; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table 3. Reduced Form Estimation: Robustness Results (cont.)
[*Educ* = L_s/L_u; Sample Period: 1970–2000]

Dependent Variable	L_{s0}/L_{u0} (1a) 2SLS 1st stage	*Income* (1b) 2SLS 2nd stage	L_{s2}/L_{u2} (2a) 2SLS 1st stage	*Income* (2b) 2SLS 2nd stage	*Wgt* L_{s1}/L_{u1} (3a) Panel 1st stage	L_{s1}/L_{u1} (4a) Panel 1st stage
Constant	10.522** (2.49)	4.404* (1.89)	7.785 (1.60)	6.263** (2.71)	1.812 (0.58)	1.322 (0.40)
Gini	−2.210*** (−4.02)		−2.121*** (−3.35)		−0.169 (−0.34)	−0.121 (−0.23)
Poor	−1.542*** (−3.99)		−1.636*** (−3.67)		−0.537* (−1.83)	−0.837*** (−2.67)
L_s/L_u		0.782*** (4.71)		0.788*** (5.18)		
Invest		0.398** (2.13)		0.436** (2.57)		
$(n + g + \delta)$		−2.203*** (−2.78)		−1.050 (−1.34)		
Latin		−0.234 (−0.99)		−0.162 (−0.73)		
Asia		0.032 (0.12)		−0.188 (−0.81)		
Adj. R^2	0.47	0.66	0.45	0.71	0.34	0.35
Obs.	46	46	46	46	145	145

Notes: *Educ* takes alternative measures of skilled to unskilled workers, L_s/L_u, as defined in Appendix A. Except for dummies, all variables are expressed in logs. Estimation is done by 2SLS; columns (1a) and (1b) report results from the first- and second-stage regressions, respectively using L_{s0}/L_{u0}; columns (2a) and (2b) report results from the first- and second-stage regressions using L_{s2}/L_{u2}; column (3a) reports results from the first-stage panel regression with weighted skilled to unskilled workers; column (4a) reports results from the first- stage panel regression with unweighted skilled to unskilled workers but with the same number of observations as in the model with weighted L_{s1}/L_{u1}. t-values are in parentheses; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Appendix A: Details on the construction of skill-to-unskilled variable (L_s/L_u)

Since there are three levels of education (primary, secondary, and tertiary), we could construct three different measures of skilled labor. Nonetheless, we follow Duffy, Papageorgiou, and Perez-Sebastian (2004) and Caselli and Coleman (2006) in considering six alternative measures of skilled labor: a) workers who have attained complete tertiary education (L_{s0}), b) workers who have attained at least some tertiary education (L_{s1}), c) workers who have attained at least complete secondary education (L_{s2}), d) workers who have attained at least some secondary education (L_{s3}), e) workers who have attained at least complete primary education (L_{s4}), and f) workers who have attained at least some primary education (L_{s5}).

Given these six measures, the corresponding measures of unskilled labor can be calculated residually. For example, if skilled labor is defined as in (a), then unskilled labor is defined as any workers who have not completed tertiary education. Similarly, if skilled labor is defined as in (b), then unskilled labor is defined as any workers who have not attained any tertiary education. Of all these alternative measures of skilled labor plus workers who have not received any education at all (L_u), workers who have attained at least some and complete primary education (L_{s5} and L_{s4}) account for a large bulk of all workers in our 46-country sample over the period 1970–2000 (see Table A1).

Table A1: Relative Size of Alternative Measures of Skilled Labor

Year	L_{s0}	L_{s1}	L_{s2}	L_{s3}	L_{s4}	L_{s5}	L_u
1970	50.81 (1.74)	83.67 (2.86)	200.59 (6.85)	345.59 (11.80)	659.13 (225.51)	964.33 (32.93)	624.19 (21.32)
1980	102.92 (2.49)	171.51 (4.14)	415.33 (10.03)	644.32 (15.56)	870.53 (21.03)	1228.43 (29.67)	707.19 (17.08)
1990	179.53 (3.33)	292.73 (5.43)	555.56 (10.30)	863.10 (16.01)	1165.35 (21.61)	1582.95 (29.36)	752.57 (13.96)
2000	255.07 (3.75)	417.24 (6.14)	743.11 (10.93)	1127.74 (16.59)	1507.42 (22.17)	2043.99 (30.06)	704.67 (10.36)
Average	147.08 (3.05)	241.29 (5.01)	478.65 (9.94)	745.19 (15.48)	1050.61 (21.82)	1454.92 (30.22)	697.16 (14.48)

Notes: Entries in the cells and parentheses are the number of workers (in thousands) and their percentages (in percentage points), respectively.

Appendix B: Additional Estimation using Alternative Measures of Skill-to Unskilled Variable (L_s/L_u)

Table B1. Reduced Form Estimation: Additional Alternative Measures of Skilled Labor
[*Educ* = L_s/L_u; Sample Period: 1970–2000]

Dependent Variable	L_{s3}/L_{u3} (1a) 2SLS 1st stage	*Income* (1b) 2SLS 2nd stage	L_{s4}/L_{u4} (3a) 2SLS 1st stage	*Income* (3b) 2SLS 2nd stage	L_{s5}/L_{u5} (4a) 2SLS 1st stage	*Income* (4b) 2SLS 2nd stage
Constant	4.561 (0.86)	8.913*** (3.46)	3.110 (0.63)	9.420*** (3.64)	−3.359 (−0.48)	15.334*** (3.39)
Gini	−2.122*** (−3.05)		−1.990*** (−3.08)		−2.431** (−2.68)	
Poor	−1.487*** (−3.04)		−1.804*** (−3.97)		−1.937*** (−3.17)	
L_s/L_u		0.813*** (5.17)		0.782*** (5.41)		0.698*** (4.06)
Invest		0.624*** (3.99)		0.462*** (2.82)		0.468** (2.15)
$(n + g + \delta)$		0.317 (0.35)		0.639 (0.69)		3.169* (1.87)
Latin		−0.287 (−1.35)		−0.052 (−0.23)		−0.742** (−2.54)
Asia		−0.345 (−1.55)		−0.149 (−0.66)		−0.033 (−0.10)
Adj. R^2	0.44	0.72	0.61	0.72	0.67	0.51
Obs.	46	46	46	46	43	43

Notes: *Educ* takes alternative measures of skilled to unskilled workers, L_s/L_u, as defined in Appendix A. Except for dummies, all variables are expressed in logs. Estimation is done by 2SLS. Columns (1a) and (1b) are based on L_{s3}/L_{u3}; columns (2a) and (2b) on L_{s4}/L_{u4}; columns (3a) and (3b) on L_{s5}/L_{u5}. t-values are in parentheses; ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.