Income Inequality, TFP, and Human Capital*

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A fruitful recent theoretical literature has related human capital and technological development to income (and wage) inequality. However, empirical assessments on the relationship are relatively scarce. We relate human capital, total factor productivity (TFP) and openness to inequality and discover that, when countries are assumed to be heterogeneous and dependent cross-sections, human capital is the most robust determinant of inequality, contributing to increasing inequality, as predicted by theory. TFP and openness turned out to be non-significantly related to inequality. These results are robust to a number of robustness tests on specifications and data and open up the prospect of theoretical research on the country-specific features conditioning the effect of human capital, technology and trade on inequality.

I Introduction

Understanding the causes of inequality is fundamental to indicating possible policy measures to ensure that the increased production and income of societies can be better shared among the whole population. Reducing inequality is important not just to achieve a fairer distribution of income and address the social concerns that widening disparities in income raise, but also to ensure a good environment for growth. As has been seen in some countries, these social concerns can lead to social instability. Income inequality may itself limit the growth potential of economies as social, economic and political instability caused by inequality is associated with slower growth. Even in democracies, an increase in inequality may contribute the election of politicians who are against openness and globalization, which may deter the world integration process which is known to have a positive effect on the growth prospects of the economy.

This paper contributes to our knowledge of the relationship between human capital, technology and inequality in two crucial ways: first, it uses a large database on inequality, based on the Standardized World Income Inequality database, and combines it with the most recent data for human capital and total factor productivity (TFP) to explain cross-country patterns of inequality; second, for the first time, it takes into account country heterogeneity, cross-country dependence, and endogeneity to common factors in evaluating the effects of human capital and TFP on inequality. The exploration of a large dataset of over 150 countries across more than 50 years (since 1960)

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JEL classifications: I24, I32, O10, O33, O50

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allowed us to explore issues such as panel heterogeneity, cross-country dependence and time-series features, such as stationarity and causality, which are absent from earlier contributions.

There is a fruitful theoretical literature seeking to explain the rise of inequality in the second half of the twentieth century (mainly in the USA) together with the rise in the supply of human capital. Skill-biased technical change and capital–skill complementarity have been crucial in explaining this phenomenon. Generally, according to this theory, skill premiums increase due to two effects. First, the skill premium would reflect the productivity difference between sectors. Second, with full capital mobility, factor price equalisation requires capital to flow to the sector operating the new technology, and thus workers in the new technologies sectors are endowed with more capital, which boosts their relative wages (Acemoglu, 2002a,b, 2003). An alternative line of reasoning has argued that the spread of information technologies (general-purpose technologies) may have raised the demand for adaptable skilled workers and made vintages of capital more adaptable. Therefore, this increases the premium for workers who show a lower learning cost and can adapt quickly from one sector to another. These ideas have been formalised by Galor and Tsiddon (1997), Greenwood and Yorukoglu (1997), Caselli (1999), Galor and Moav (2000) and Aghion et al. (2002). Theoretically, skill-biased technological change is explained by the proportion of skills (education) in the economy, and wage inequality (typically measured by the wage ratio between skilled and unskilled workers) is proportional to the proportion of skills in the economy. Education is thus seen in the theory as a determinant of more technical change (and consequently growth) and more inequality.

Whatever the explanation for the rise in inequality and its relationship to technology and human capital, there is little quantitative literature on the issue, as pointed out by Hornstein et al. (2005) p. 1361. In fact, empirical attempts to evaluate the relationship are mostly country-specific; see, for example, Ding et al. (2011) and Ratto and Stokke (2013) dealing with the effect of technology, and Birchenall (2001) dealing with the effect of human capital. Micro-evidence on the relationship between education and income inequality is mixed. While Martins and Pereira (2004) found a positive sign for the effect of education returns on inequality due to an increase in returns to education throughout the wage distribution for 16 European countries, Wang (2011) found returns to education in China that are more pronounced for individuals in the lower tail of the earnings distribution than for those in the upper tail, in stark contrast to the results found in some developed countries.

We have found a handful of papers that evaluated this relationship using a large cross-section of countries. Some of these papers are solely concerned with the relationship between education and inequality. Milanovic (1994) reassessed the initial contribution of Kuznets (1955), adding institutional variables to the analysis of determinants of the income inequality. Teulings and van Rens (2008) found evidence for a negative relationship between increase in schooling and returns in a cross-section of countries, implying a contribution of schooling to the reduction of inequality, a result in the same direction as that obtained by De Gregorio and Lee (2002).

Three other papers relate income inequality in cross-sections with several controls, among which particular attention is given to education, technology, openness and institutions. Barro (2000) presents fixed-effects estimations of equations for the Gini index on covariates such as GDP and GDP squared, schooling, democracy index, openness, rule of law index and several dummies. In his fixed-effects estimations, dummies for income or spending and secondary schooling are negatively related to inequality, and higher schooling and openness are positively related to inequality (with significant coefficients). Primary schooling and the dummy for individual or household data are non-significantly related to the Gini coefficient. There is a strong inverted-U relationship with GDP (the so-called Kuznets curve) in Barro’s estimations. Rodriguez-Pose and Tselios (2009) present positive and robust signs for secondary and tertiary education levels and income inequality among European regions. Additionally, these authors found that population ageing, female participation in the labour force, urbanisation, agriculture and industry are negatively associated to income inequality, while unemployment and a specialisation in the financial sector positively affect inequality. Finally, income inequality is lower in social-democratic welfare states, in Protestant areas, and in regions with Nordic family structures. Recently, Jaumotte et al. (2013) reassessed the determinants of inequality. They focus on the effect of globalisation on inequality but avoid the relationship between inequality and GDP.
conclude that trade globalisation decreases inequality while financial globalisation increases inequality. Moreover, information and communication technologies and credit deepening increase inequality, while the share of industry in the economy decreases inequality. Interestingly, education variables and initial GDP (when included) are non-significantly related to inequality.

As may be noted, empirical evidence from a large cross-section of countries is quite ambiguous with regard to the determinants of inequality and does not confirm theories in crucial aspects such as the influence of education and technology. However, much criticism has affected data on inequality around the world. In fact, greater coverage across countries and over time is available from these sources only at the cost of significantly reduced comparability across observations. There are currently three different projects that collect and make publicly available inequality data for many countries and periods around the world: the Luxembourg Income Study (LIS); the dataset assembled by Deininger and Squire (1996) for the World Bank (WIID), recently updated and upgraded by the World Institute for Development Economic Research (WIDER) project; and the most recent Standardized World Income Inequality dataset (SWIID), by Solt (2009). The LIS, which was used by Jaumotte et al. (2013), has generated the most comparable income inequality statistics currently available but covers relatively few countries and years. The Deininger and Squire dataset and its successors, used by Barro (2000), on the other hand, provide many more observations, but only at a substantial loss of comparability. Solt (2009) implemented a sequence of steps in order to standardise income inequality data and provide data with more ample coverage than the WIID but at the highest quality as in the LIS. However, in the process of standardisation, not all countries had sufficient data in the original sources. To handle this, Solt (2009) also calculated a standard error of each Gini coefficient to account for the remaining uncertainty in data. The disadvantage of using cross-country data is that they may ignore some micro-effects that can be studied in micro-data. The interesting feature of inequality data, however, is that it is based on country micro-studies on inequality. Exploring the heterogeneity of data concerning the determinants of inequality is especially important since the effects of different inequality determinants may differ considerably from country to country.

In fact, and to give a few examples, the effect of technology adoption may differ if the country is on the technological frontier or lagging behind; the effect of human capital may differ between countries where brain-drain is more evident than in others; and the effect of openness may depend crucially on the level of integration and on the market size of the country. In general, historical and institutional (e.g. labour market related) country-specific factors that are not simply captured by fixed-effects estimations, are in fact dealt with through heterogeneous panel estimations.

Our main conclusions point to a clearly significant positive effect of human capital on inequality, an effect that is relevant worldwide but stronger for the developed world. In contrast, our results indicate that the effects of technology and openness are not statistically significant, as well as dependent on different specifications. Overall, the common factors framework dismisses the existence of a Kuznets curve.

The rest of this paper is organised as follows. In Section II we describe our dataset. In Section III we describe our estimation strategy. In Section IV we present our results, beginning with detailed evidence for cross-country dependence, stationarity, and evidence of (Granger) causality and then showing the results from several different specifications based on heterogeneous panels methods. Section V concludes.

II Sources and Data

We use data from the SWIID, version 4.0, from Solt (2009), for the Gini coefficient.1 2 These include data on the Gini coefficient using post-

1 Available at http://thedata.harvard.edu/dvn/dv/fsolt/faces/study/StudyPage.xhtml?studyId=36908.

This is the first time this source of inequality data has been used to assess the relative importance of the determinants of inequality. We explained above the reasons why this choice is superior to the previously used data.

2 In a working paper version of this article, we compare some of our results with inequality data from the Word Income Inequality database (WIID2c). In doing so, we follow strict criteria for the selection of data, separating Gini coefficients from net income, consumption and gross income and preferring data with wide coverage and higher quality. In that analysis, we also make clear that the SWIID has more than four times the number of observations than the measures coming from the WIID, making SWIID more suitable (if not uniquely suitable) for study with heterogeneous panel data methods.
taxes and post-transfer income (the net definition) and on the Gini coefficient using pre-taxes and pre-transfer income (the market definition), and the respective standard errors by country and year. Previous data on inequality have presented variables divided by the type of underlying measure of inequality (income or consumption) and by the quality of data (e.g. defining different quality levels). Solt (2009) maintained the same concerns within his dataset. He divides his data into net and market Gini indexes which may be roughly matched with consumption and (net) income Gini indexes, on the one hand, and (gross) income Gini indexes, on the other hand. Additionally, he provides standard deviations for his data, in order to be able to measure uncertainty in the data, basically due to less availability of underlying data to calculate inequality measures in some countries. Thus, this can be interpreted as information on the quality of the underlying data. In most of the analysis carried out in this paper, we will use a quality-adjusted measure of the SWIID Gini coefficient which is obtained simply by dividing the Gini coefficient by the respective standard deviation, provided by Solt (2009).3

We use GDP per capita, openness, the Human Capital Index, and the TFP index from Penn World Tables (PWT), version 8.0 (Feenstra et al., 2013).4 Human capital in PWT 8.0 is measured by a ‘Mincerian’ combination of years of schooling (from Barro & Lee, 2013, version 1.3) and returns to education. The results from Psacharopoulos (1994) show that returns from schooling decrease across years of schooling. As the influence of human capital on inequality arguably changes through years of schooling (Barro’s results show negative signs for primary and secondary schooling and positive signs for tertiary schooling) and returns from schooling are essential to understand income inequality, we think this variable is the most appropriate human capital measure to enter in inequality regressions. In fact, as human capital measures corrected for returns from education assign higher weight to lower levels of education, they correct underestimations of human capital in less developed countries. Lower levels of education in less developed countries may have more influence in decreasing wage inequality than they have in more developed countries. The human capital measure provided by the PWT 8.0 is the one with the highest coverage up to now, as it not only corrects years of schooling by different returns by levels of education, but also is interpolated to provide annual measures. It is worth noting that returns to education differ between levels of education but not between different countries or years as these alternatives would result in lower coverage.

TFP is available in PWT 8.0 both as a ratio to the USA=1 level and at constant national prices. We construct our index departing from a final TFP level (related to the USA) in 2011 and then deflating year by year using growth rates of the national currency measure of TFP. This allows us to have a PPP measure of TFP that is independent of the US level (on a year-by-year basis) in the time-series analysed.5 Contrary to Barro (2000) but similar to Jaumotte et al. (2013), we used annual data.

We end up with an unbalanced panel database of 156 countries with an average of 31 years per country, from 1960 to 2011.6 Table 1 shows descriptive statistics for the variables included in the analysis.

### III Estimation and Methods

The first issue to deal with when it comes to estimation is the choice of explanatory variables for the equation for inequality. The theory explains inequality through skill-biased technical change, and thus human capital and technology seem to be the main theoretical determinants of inequality. Additionally, openness to trade in the theory increases inequality, also suggesting that the openness ratio may be considered also as a determinant of inequality. Thus, the theory points to three main determinants of inequality: human capital, technology and openness (Acemoglu, 2002a,b). One must note, however, that according to the theory, technology is endogenous as the

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3 The uncertainty-corrected measure is $\text{GINI}/\text{sd (GINI)}$, where $\text{GINI}$ is the Gini index provided by SWIID and $\text{sd(GINI)}$ is the standard deviation of the Gini index, also provided by the SWIID, which corrects for uncertainty or measurement error within the sources. Later on, on the Discussion section, we discuss the results obtained with an alternative uncertainty-corrected measure.

4 Available at http://www.rug.nl/research/ggdc/data/penn-world-table.

5 We began with the year 2011 in order to maximise the available data for the TFP index.

6 There are an average of 31 observations per country for the pool of variables mentioned, although some variables may include nearly 50 years per country.
direction of technical change is also determined by human capital. Observation of previous empirical contributions from Barro (2000) and Jaumotte et al. (2013) suggests that common regressors should be linked with technology, human capital and openness. While Barro (2000) also includes estimation of the Kuznets curve, rule of law and democracy indexes and several dummies, Jaumotte et al. (2013) include several variables for trade and financial globalisation, shares and productivity series for industry and agriculture and private credit. Chakrabarti (2000) studied the effect of openness to trade on inequality but does not consider the effects of human capital and technology explicitly. We choose to estimate a more parsimonious specification. 7 Our estimation method hereinafter is the common factor framework for heterogeneous panels from Pesaran (2006) and followers. Our baseline specification is thus as follows:

\[
gini_{it} = \beta_1 hcap_{it} + \beta_2 TFP_{it} + \beta_3 Open_{it} + \xi f_i + z_i + u_{it} \tag{1}
\]

where \( gini \) is the natural logarithm of the Gini coefficient, \( TFP \) is the natural logarithm of a measure of total factor productivity, \( hcap \) is the the natural logarithm of the human capital variable, \( Open \) is the the natural logarithm of the openness ratio, \( z_i \) is the country fixed effect, \( f_i \) is the vector of unobservable common factors, \( \xi f_i \) is the associated vector of factor loadings and \( u_{it} \) is the error term. As can be observed from (1), each coefficient is country-specific, thus allowing for complete heterogeneity in the estimation. In particular, the empirical model incorporates the fact that country-specific factors (such as institutions) affect the effects of human capital, TFP and openness in inequality. Additionally, as each regressor can also depend on the common factor, the method is robust to endogeneity of the observable factors towards the common factors determining inequality. As Pesaran and Tosetti (2011) explain, this method is robust to non-stationarity in both observables and non-observables and works well in the presence of weak and/or strong cross-sectionally correlated errors. 8

As the analysis in Jaumotte et al. (2013) might indicate, we suspect that the Gini coefficients, financial openness, and technological development may well be non-stationary and heterogeneous among different countries. Finally, we may consider that technology adoption is being

| Variable               | No. of obs. | Mean   | SD    | Min   | Max    |
|------------------------|-------------|--------|-------|-------|--------|
| Gini (net)             | 4,597       | 3.5923 | 0.2960| 2.7324| 7.3871 |
| Gini (market)          | 4,597       | 3.7395 | 0.2234| 2.8367| 4.3740 |
| Gini (net) – value/SD  | 4,597       | 3.5613 | 0.9786| 1.2658| 9.5894 |
| Gini (market) – value/SD| 4,597       | 3.2479 | 1.0049| 1.0747| 9.5410 |
| Human capital          | 6,797       | 0.6905 | 0.3160| 0.0198| 1.2861 |
| TFP                    | 4,994       | 0.5254 | 0.5287| –3.5389| 1.1222 |
| Openness               | 7,760       | 1.1645 | 1.1020| –12.7415| 3.2061 |
| GDP per capita         | 7,760       | 8.2779 | 4.8890| 4.8890| 10.9961 |

Notes: Gini variables are from SWIID (Solt, 2009). In the source, Gini variables are measured from 0 to 100%. Human capital, TFP, openness = (Exports + Imports)/GDP, and GDP per capita are from PWT 8.0. value/SD means that the Gini coefficient is divided by its standard error, a measure to account for uncertainty in the data for each country–year pair. All variables are in natural logarithms.

7 We performed specification testing against the existence of the Kuznets curve (GDP per capita and GDP per capita squared), and our results indicate that those variables are not significant when added to our benchmark specification. Additionally, the inclusion of GDP per capita as a explanatory variable for inequality would imply obvious multicollinearity with other variables, such as human capital and TFP. These results are available upon request.

8 There are not many empirical applications with those heterogeneous panel methods. Notable exceptions are the recent papers from Markus Eberhardt and co-authors (Eberhardt & Teal, 2013a,b; Eberhardt & Presbitero, 2015; and Eberhardt et al., 2013). Eberhardt and Teal (2011) explain why the standard cross-country regression framework and its panel cousins need to be reconsidered. None of these papers deal with income inequality.
determined by the same phenomena as inequality, say by common factors such as globalisation or the entry of China into the world market, technology thus being an endogenous variable. Additionally, inequality evolution in each country might be hit by common shocks (such as the oil shocks in the 1970s or the current financial/sovereign debt crisis). These are the reasons why we will apply the Pesaran (2006) estimator for heterogeneous panels.

IV Empirical Results

Our results section begins by presenting evidence of the time-series properties of inequality. Due to imbalance and holes in several time series, to perform some of those tests, we limit our variable of interest such that we include only countries with more than a given number of time-series observations (30) in the Gini index series. We consider both the Gini coefficient as provided by the source as well as an uncertainty-corrected version of the Gini coefficient which involves dividing the coefficient by the standard deviation (also provided by the source).

These new data on inequality provide, for the first time, the means for analysing time-series features in a reasonable set of countries. This analysis occupies Sections IV.i and IV.ii. Then, in Section IV.3 we present evidence on the relationship between human capital, TFP and openness in inequality in a heterogeneous panel set-up. Section IV.iv presents results for a number of different sub-samples of countries. Section IV.v present results for alternative specifications. Section IV.vi addresses a number of robustness analyses and discusses the results.

9 For complete arguments towards reconsideration of traditional econometric methods to study moderate-T dimensional panel data of countries, see Eberhardt and Teal (2011).

10 This would be the minimum number of time-series observations for the Gini index. However, due to the unbalanced nature of the panel, the observations that effectively enter in regressions may be fewer than 30.

11 It should be noted, however, as stressed by Eberhardt and Teal (2011), that most of the unit-root and cointegration tests have low power in panels of moderate dimension such as the one under analysis. This does not invalidate the fact that their results constitute important motivation to choose a heterogeneous common factor approach that is indeed appropriate to deal with moderate N, moderate T panels, typical in macroeconomic analyses.

(i) Initial Analysis: Cross-Country Dependence and Stationarity

The standard literature on panel data analysis assumes cross-sectional independence. However, there are several reasons why cross-sectional dependence can arise in large panel data on countries. Such cross-correlations can arise due to omitted common factors that affect the evolution of inequality, including technological cross-country spillovers, migration of workers, integration into international markets and international shocks. As Pesaran and Tosetti (2011) write, ‘conditioning on variables specific to the cross-section units alone does not deliver cross-section error independence, an assumption required by the standard literature on panel data models’, and one that has been applied in the existing analyses of the determinants of inequality. Table 2 shows results for the cross-sectional dependence test from Pesaran (2004) which tests the null of no cross-sectional dependence.

These tests constitute overwhelming evidence that the series of inequality (as well as their main determinants) are cross-country related, thus inducing bias on estimations assuming cross-country independence. It is interesting to note that the series with the highest cross-dependence test is human capital, followed by openness. Also worth noting is that the uncertainty-corrected measures of the Gini coefficient present higher values for the test than the original Gini coefficients, indicating an increased correlation between countries in these uncertainty-corrected measures. Although we provide results from the Gini coefficient from the market approach in Table 2, from now on we will concentrate on the most interesting variable: the Gini coefficient from post-tax and post-transfer income. This variable incorporates the effects of progressive tax systems and is close to a measure of inequality related to disposable income.12

12 Variables linked with disposable income have also been the focus of earlier papers. Barro (2000) uses a dummy to account for differences from the net income and consumption definition and gross income definition. This dummy is highly significant, indicating that these variables in fact measure different phenomena. Jaumotte et al. (2013) p. 276 also express concern about jointly analysing income- and expenditure-based Gini indexes. Results obtained with the market Gini coefficient (and its uncertainty-corrected version), which can compare with the ones presented in the paper, can be provided by the authors.
Another issue to be dealt with is the integration level of the series, that is, its stationarity or non-stationarity. It is well known that most macro time series are non-stationary even though the issue has received virtually no attention in traditional panel regression analyses (Phillips & Moon, 2000, p. 264). The graphic analysis in Jaumotte et al. (2013) pp. 277–83 is a means of observing non-stationarity of Gini coefficients and their determinants. Table 3 shows unit-root tests. We use the Pesaran (2007) panel unit-root test whose null is that the variable is I(1). The analysis of results – with the majority of the tests on the level variables not rejecting – points to the non-stationarity of the Gini coefficients and some of their determinants, with particularly clear results for human capital. The only determinant of inequality for which the tests clearly reject non-stationarity is openness. These results are confirmed by the tests on the differenced variables (see Table A.1), which clearly reject the unit-root case.

This section provides clear empirical motivation that the heterogeneous panels unobserved common factors framework from Pesaran (2006) and followers is appropriate to analyse inequality determinants. The availability of data in quality and quantity allows for the correct implementation of the framework.

The next section explores the causal relationship between inequality and human capital

(ii) Initial Analysis: Causality between Education and Inequality

Trade and productivity (or technology) as determinants of inequality have been widely studied and the causal relationship from openness and technology to inequality is well founded in theory (see Richardson, 1995; Chakrabarti, 2000; Horstein et al., 2005). However, the causality path from human capital to inequality is not so well founded. Despite the tremendous emphasis on the role of human capital in the skill-biased technological change and general-purpose technology literatures, there are some microeconomic arguments from the economics of education field suggesting that inequality may decrease incentives to educate and thus decrease human capital (Gutiérrez and Tanaka 2009; Stocké et al., 2011) are good examples that emphasise the causality channel from inequality to education. It is important then to evaluate evidence in our data from the causality channel between human capital and inequality. We do this using a cointegration test for the null of no cointegration, the Westerlund (2007) test. Table 4 presents the tests when the causality is evaluated between human capital and the uncertainty-corrected Gini coefficient. The intuition is as follows. If the null is rejected for a test in which the dependent variable is inequality and simultaneously the null is not rejected for a test in which the dependent variable is human capital, then human capital has a (Granger) causal effect on inequality and inequality has no (Granger) causal effect on human capital. The pattern of results clearly suggests a (Granger) causal relationship from human capital to inequality and not the other way around, tending to validate an empirical strategy that estimates the relationship theoretically implied by the skill-biased technological change framework. This is valid for both the uncertainty-corrected measure presented in Table 4 and the

| Variable                  | Gini net income (>30) | Gini market income (>30) | Gini net income (>30, /SD) | Gini market income (>30, /SD) | Human capital | TFP | Openness |
|---------------------------|-----------------------|--------------------------|---------------------------|-----------------------------|----------------|-----|----------|
| CD test                   | 23.33***              | 19.79***                 | 96.40***                  | 79.47***                    | 554.05***      | 53.81*** | 240.32*** |
| P-value                   | (0.000)               | (0.000)                  | (0.000)                   | (0.000)                     | (0.000)        | (0.000) | (0.000)  |
| Number of countries       | 82                    | 82                       | 82                        | 82                          | 128            | 106  | 155      |

Notes: >30 indicates that only cross-sections with more than 30 time-series observations are included. Level of significance: ***p<0.01. /SD indicates that the Gini coefficient is divided by the source standard deviation to account for data uncertainty. All variables are in natural logarithms.

13 An example in the literature that uses this test to motivate the underlying channel of causality is Eberhardt and Presbitero (2015).
As in previous tests, we use only cross-sections that have availability of time-series data of 30 or more periods.

The next subsections present results for the influence of human capital, TFP, and openness on inequality using heterogeneous panels methods.

(iii) Results: Baseline Specification

In this subsection we present the results for our baseline specification in Equation (1).

Results in Table 5 show that, for uncorrected Gini indexes, human capital, TFP and openness are not quite significant, which may mean that there is great heterogeneity concerning effects of the three determinants across countries. Human capital is significant only in the regression for the Gini coefficient – with a negative sign when the Gini coefficient is not corrected for uncertainty and for the restricted sample with longer time-series within panels (Table 5, column (2)), and with a positive sign when the Gini coefficient is corrected for uncertainty (Table 5, columns (3) and (4)). In the former case, an increase of 1 per cent in human capital would imply a decrease of 0.27 per cent in the uncorrected Gini coefficient. In the latter, however, a 1 per cent increase in human capital would increase the corrected Gini coefficient from 2.4 per cent to 3.7 per cent. Alternatively, it can be said that for the same level of precision of the Gini coefficient, a 1 per cent increase in human capital would increase the Gini coefficient by values ranging from 2.4 per cent to 3.7 per cent. The variability of effects across countries can be observed by the count of significant effects by country, provided in the table. The number of countries with significant results for each variable is usually more than 50

14 Results for the uncorrected measure are in Table A.2.
per cent of the number of countries included in the regressions. While the overwhelming number of countries present significant positive coefficients for human capital, the numbers of significantly positive and negative coefficients for TFP and openness are relatively balanced, possibly indicating the great variability in the relationship between TFP and openness and inequality between countries. 15

(iv) Results: Sub-samples

In order to evaluate the effects of human capital, TFP, and openness in different groups of countries, we now split our sample according to the level of income, inequality, human capital, TFP and openness. We thus aim to analyse in depth the heterogeneity in this equilibrium relationship between inequality and its determinants. We use the sample median for real GDP per capita, the (corrected) Gini index, human capital, TFP and openness as the thresholds to split the sample in each case. For example, a country with an average of GDP per capita above the median would be classified as a rich country.

Results in Tables 6–8 show that the positive effect of human capital on inequality, once it is corrected for uncertainty in the data, occurs mainly in rich countries, in countries with high human capital and in countries with high TFP. In these countries a 1 per cent increase in human capital would imply an increase in the corrected Gini coefficient from 3.2 per cent to 4.8 per cent. The fact that the positive effect of human capital in inequality is particularly evident in the group of rich countries is consistent with the skill-biased technical change theory, according to which the increase in human capital stocks should be associated with the adoption of skill-biased technologies, which in turn positively influence the wages of the richest in the economy. This effect may overcome the supply effect and is present mostly in the rich countries (see

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| Table 4 | Cointegration Tests |
|---------|---------------------|
|         | (1)     | (5)     | (6)     | (7)     | (8)     |
|         | Lag     | Trend   | Gt test | Ga test | Pt test | Pa test |
| Dependent variable | Gini coefficient net income (≥30, /SD) |  |
| p-value | 1       | No      | –2.400*** | –10.22*** | –9.630*** | –9.588*** |
| P-value | 1       | Yes     | –2.653**  | –12.64   | –10.79   | –11.343** |
| P-value | 2       | No      | –2.353*** | –8.232   | –7.195   | –7.261*** |
| P-value | 2       | Yes     | –2.689**  | –10.952  | –7.660   | –8.500    |
|         |         |         |         |         |         |         |
| Dependent variable | Human capital |  |
| P-value | 1       | No      | –1.826   | –3.711   | –5.713   | –1.453    |
| P-value | 1       | Yes     | –1.990   | –7.607   | –9.765   | –6.089    |
| P-value | 2       | No      | –1.879   | –3.855   | –5.448   | –1.406    |
| P-value | 2       | Yes     | –1.807   | –7.110   | –8.696   | –5.479    |

Notes: >30 indicates that only cross-sections with more than 30 time-series observations are included. Level of significance: *** p < 0.01; ** p < 0.05. /SD indicates that the Gini coefficient is divided by the source standard deviation to account for data uncertainty. All variables are in natural logarithms. Rejection of H0 in Ga and Gt tests should be taken as evidence of cointegration of at least one of the cross-sectional units. Rejection of H0 in Pa and Pt tests should therefore be taken as evidence of cointegration for the panel as a whole.

15 We follow Eberhardt and Presbitero (2015) in showing counts of significant effects. However, due to the fact that we cannot rely on country-specific estimates of standard errors, we do not analyse the effects of each country. Alternatively, we construct sub-samples of countries to explore that heterogeneity in depth.
In the high-human-capital sample and in the low-TFP sample, we obtain a negative statistically significant effect of TFP on inequality, which is not confirmed in the other sub-samples.

Table 9 shows results for regressions of subsamples of high-inequality countries and low-inequality countries. The stronger result is confirmed for high-inequality countries, but we have also obtained a statistically significant result for low-inequality countries (in the restricted sample, column (4)). In this case, a 1 per cent increase in human capital would imply that the corrected Gini coefficient increases 1.2 per cent.

Finally, Table 10 shows results for regressions of sub-samples of countries with high openness to trade and low openness to trade. In this case we obtain a slightly higher effect of human capital in inequality in highly open countries than that obtained for countries with less openness to trade.

However, the effect of human capital is highly significant in both groups of countries. While in the group of countries highly open to trade a 1 per cent increase in human capital would imply an increase in the corrected Gini coefficient from 3.3 per cent to 4.8 per cent, in the group of countries less open to trade a 1 per cent increase in human capital would imply an increase in the corrected Gini coefficient from 2.2 per cent to 2.7 per cent.

Below, we present a set of robustness analyses to evaluate the effect of human capital and TFP on inequality, using the uncertainty-corrected measure of the Gini coefficient.

(v) Results: Alternative Specifications

In the robustness analysis we have implemented slightly modified common correlated effects estimators as suggested in recent literature. We include in regressions one or more further covariates in the form of cross-section averages, which
helps to identify the unobserved common factors (in the spirit of Pesaran et al., 2013). Moreover, we also follow Chudik and Pesaran (2013) in introducing lags of cross-section averages in order to account for possible feedback effect from inequality to human capital.16

To this end, we consider openness as a cross-section average, seeking to identify the unobserved common factors as linked with globalisation and global integration (e.g. the entrance of China into the global market or the international crisis affecting all countries which can hit countries differently). Column (1) in Table 11 presents these results. In column (2) we present regressions in which we identify the common unobserved factors as not only globalisation and integration (using the variable openness as cross-section average) but also technological spillovers (using the variable TFP as cross-section average). In column (3) we add production spillovers, including GDP per capita as a cross-section average, to the set of possible unobserved common factors. In column (4) we consider only openness as cross-section average and eliminate TFP from the regression. This regression aims to show that the robustness of the positive effect of human capital on inequality is not dependent on the presence of TFP, and thus not dependent on the way this particular TFP measure is calculated. In columns (5) and (6) we also include lags of the cross-section averages.17

In this robustness analysis we consider as dependent variable the Gini coefficient (net definition), using only cross-sections with 30 or more time-series observations. This is done to allow for diagnostic testing. We will also describe the results obtained with the same variable from all the cross-sections (independently of time-series coverage).

In regressions in which production spillovers are not considered as a cross-country common factor (columns (1), (2) and (4)) the effect of human capital is highly significant, meaning that

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**Table 6**

| Rich sample |     |     | Poor sample |     |
|-------------|-----|-----|-------------|-----|
| **(1)**     |     |     | **(2)**     |     |
| Dependent variable: Gini measure |     |     | Gini measure |     |
| hcap        | 4.043*** | 3.157*** | Gini net post-tax; post-transfer (./SD) |     |
| TFP         | −0.127 | −0.251 | Gini net post-tax; post-transfer (>30, ./SD) |     |
| Open        | 0.032 | −0.119 | Gini net post-tax; post-transfer (>30, ./SD) |     |
| No. of obs. | 1,657 | 1,431 | 1,643 | 1,162 |
| Avr. no. of obs. | 36.8 | 40.9 | 28.3 | 35.2 |
| Min–max     | 12–52 | 22–52 | 7–48 | 21–48 |
| No. of countries | 45 | 35 | 58 | 33 |
| Wald        | 9.77** | 9.98** | 1.52 | 1.52 |
| CD test (res) | – | −1.40 (0.162) | – | −0.79 (0.430) |
| Stat test (res) | – | reject I(1) | – | reject I(1) |

**Notes:** Dependent variables are natural logarithm of the Gini coefficients. All variables are in natural logarithms. hcap is human capital, TFP is total factor productivity and Open is Openness ratio. A constant is included in all regressions but omitted from the Table. Values in parentheses below coefficients are $P$-values from robust (clustered) standard errors. Level of significance: ***$P$<0.01; **$P$<0.05. Wald test is a joint significance test for the regressors. CD test is a Pesaran (2004) cross-section dependence test on the null of cross-section independence carried out on the residuals from the regression ($P$-values in parentheses). Stat test is the Pesaran (2007) unit-root test carried out on the residuals. This test used 3 lags, and ‘reject I(1)’ means that in all lags the test of unit root rejects. (./SD) indicates that the Gini coefficient is divided by the source standard deviation to account for data uncertainty.

16 This is similar to what Eberhardt and Presbitero (2015) did in an empirical implementation for the relationship between growth and debt.

17 We closely follow the rule of thumb suggested by Chudik and Pesaran (2013), $p=T^{1/3}$, and include 3 or 4 lags of the cross-section averages.
a 1 per cent increase in human capital would imply a rise in the level of inequality of around 3.8 per cent. From these, columns (1) and (2) present residuals that show no evidence of non-stationarity or cross-country dependence. Regression residuals from column (4) present some evidence of cross-country dependence (yet much lower than in the regressors) and no evidence of non-stationarity. In fact, as in Eberhardt and Presbitero (2015), the introduction of additional cross-country averages in regressions helps to obtain cross-country independence of residuals. In the regression that includes production spillovers as a possible common factor (column (3)) the effect of human capital decreases quantitatively but maintains the high level of significance. In this case, a 1 per cent increase in human capital would imply a rise in the level of inequality of around 1.9 per cent. Additionally, residuals show no evidence of cross-country dependence or non-stationarity. For regressions robust to potential feedback effect from inequality to human capital (columns (5) and (6)) the effect of human capital is also significantly positive with comparable absolute effects (3.31 per cent and 2.97 per cent, respectively) although the statistical significance is decreased from previous regressions. Wald tests point to high significance of the regressors.

Regressions that include all the cross-sections (and not only those with high time-series coverage, as in Table 11) would confirm those results. Regressions corresponding to those in columns (1), (2) and (4) slightly decrease the effect of human capital to a coefficient from 2.8 to 3.17 (with a high significance corresponding to p-values less than 0.001). Regression corresponding to that in column (3) decreases the quantitative effect and the level of significance (to a value near 0.8 and a significance level of near 0.25). Regressions corresponding to those in columns (5) and (6) greatly increase the statistical significance of the human capital coefficient and also its absolute value, with a 4.7 per cent increase in inequality deriving from a 1 per cent change in human capital.
In this section we critically discuss our results and also present some information about additional tests that are not presented in the paper but that are available upon request. We present evidence on the effects of human capital, TFP and openness on inequality. To that end, we use a recent measure of inequality with high coverage (Solt, 2009) and also recently developed estimators that allow for country heterogeneity and are robust to country dependence, stationarity and endogeneity toward unobserved common factors (generally described in the survey by Eberhardt & Teal, 2011). We found a positive robust effect of human capital on inequality and non-significant effects of TFP and openness. We also discovered that the influence of higher human capital on higher inequality is totally dependent on correcting the Gini coefficient for its measurement uncertainty (with a measure of uncertainty provided by the source). According to Solt (2009) the provided standard error for the Gini coefficient aims to correct the remaining uncertainty in the estimations for the inequality measure. This standard error measures the remaining error due to lack of or poorer precision in the Gini coefficients. An in-depth analysis of the data reveals that such a negative sign of the coefficient for the uncorrected Gini index is due to poorer precision in Gini coefficients. For instance, restricting the regression of column (1) in Table 5 to values for the Solt (2009) standard error above the third quartile (the most imprecise Gini coefficients) would yield a coefficient of \(0.788\) (with a \(p\)-value less than 0.001), and doing the same to the regression of column (2) in the same table would yield a coefficient of \(0.596\) (with a \(p\)-value of 0.010). Thus, there is a clear need to account for these differences in the quality of the source data when assessing the determinants of inequality.

| Dependent variable | Gini measure | Gini net post-tax; post-transfer \((./SD)\) | Gini net post-tax; post-transfer \((./SD)\) | Gini net post-tax; post-transfer \((./SD)\) | Gini net post-tax; post-transfer \((./SD)\) |
|-------------------|--------------|---------------------------------------------|---------------------------------------------|---------------------------------------------|---------------------------------------------|
| **hcap**          | 3.92**       | 4.23***                                     | 0.843                                       | 2.562                                       |
|                   | (1.572)      | (1.341)                                     | (1.200)                                    | (1.730)                                    |
| **TFP**           | -0.271       | -0.424**                                    | -0.081                                     | -0.224                                     |
|                   | (0.225)      | (0.209)                                     | (0.156)                                    | (0.308)                                    |
| **Open**          | 0.153*       | 0.112                                       | -0.033                                     | -0.013                                     |
|                   | (0.088)      | (0.089)                                     | (0.043)                                    | (0.101)                                    |
| No. of obs.       | 2,162        | 1,849                                       | 1,138                                       | 744                                        |
| Avr. no. of obs.  | 34.3         | 38.5                                        | 28.4                                       | 37.2                                       |
| Min – max         | 9 – 52       | 21 – 52                                     | 7 – 48                                      | 31 – 48                                    |
| No. of countries  | 63           | 48                                          | 40                                          | 20                                         |
| Wald              | 10.69**      | 15.64***                                    | 1.35                                       | 2.74                                       |
| CD test (res)     | –            | -1.76* (0.078)                              | –                                          | -0.22 (0.825)                              |
| Stat test (res)   | –            | reject I(1)                                 | –                                          | reject I(1)                                |

**Notes:** Dependent variables are natural logarithm of the Gini coefficients. All variables are in natural logarithms. hcap is human capital, TFP is total factor productivity and Open is openness ratio. A constant is included in all regressions but omitted from the table. Values in parentheses below coefficients are \(P\)-values from robust (clustered) standard errors. Level of significance: *** \(P < 0.01\); ** \(P < 0.05\); * \(P < 0.1\). Wald test is a joint significance test for the regressors. CD test is a Pesaran (2004) cross-section dependence test on the null of cross-section independence carried out on the residuals from the regression (\(P\)-values in parentheses). Stat test is the Pesaran (2007) unit-root test carried out on the residuals. This test used 3 lags, and ‘reject I(1)’ means that in all lags the test of unit root rejects. \/(SD) indicates that the Gini coefficient is divided by the source standard deviation to account for data uncertainty.

(vi) Discussion, Robustness and Policy Implications

In this section we critically discuss our results and also present some information about additional tests that are not presented in the paper but that are available upon request. We present evidence on the effects of human capital, TFP and openness on inequality. To that end, we use a recent measure of inequality with high coverage (Solt, 2009) and also recently developed estimators that allow for country heterogeneity and are robust to country dependence, stationarity and endogeneity toward unobserved common factors (generally described in the survey by Eberhardt & Teal, 2011). We found a positive robust effect of human capital on inequality and non-significant effects of TFP and openness. We also discovered that the influence of higher human capital on higher inequality is totally dependent on correcting the Gini coefficient for its measurement uncertainty (with a measure of uncertainty provided by the source). According to Solt (2009) the provided standard error for the Gini coefficient aims to correct the remaining uncertainty in the estimations for the inequality measure. This standard error measures the remaining error due to lack of or poorer information available for some country–year pairs. Interestingly, ignoring this correction would yield a negative and significant effect of human capital on inequality, thus allegedly implying that human capital investments would decrease inequality. An in-depth analysis of the data reveals that such a negative sign of the coefficient for the uncorrected Gini index is due to poorer precision in Gini coefficients. For instance, restricting the regression of column (1) in Table 5 to values for the Solt (2009) standard error above the third quartile (the most imprecise Gini coefficients) would yield a significantly negative coefficient of \(-0.788\) (with a \(p\)-value less than 0.001), and doing the same to the regression of column (2) in the same table would yield a coefficient of \(-0.596\) (with a \(p\)-value of 0.010). Thus, there is a clear need to account for these differences in the quality of the source data when assessing the determinants of inequality.
There are two main issues that might compromise our results: the use of a certain measure of human capital; and the correction of the Gini measure with the source standard error to account for different data quality across the world. Would it be possible that this effect is linked with the specific human capital variable used in this paper? In fact, measurement of human capital has always been somewhat controversial in the literature. The measure of human capital that is most used in the literature is that of Barro and Lee (2001), which has been criticised by, for example, Cohen and Soto (2007) due to measurement errors and sources. In fact, Cohen and Soto (2007) argued that they had crucially increased the data quality when compared to their predecessors. Barro and Lee (2013), in version 1.3 of the database, updated the data to incorporate the criticism. The PWT 8.0 human capital variable used in this paper builds on the same version of the Barro and Lee database. Additionally, the authors of PWT 8.0 filled in the years between the 5-year intervals provided by Barro and Lee using linear interpolation and corrected the years of schooling to different returns from schooling by level of education following a Mincerian approach. There are, of course, some limitations to this measure, especially the fact that it does not distinguish the returns from schooling by country and by year. An exploration of the returns to schooling variability in a human capital measure would certainly be obtained at the cost of reducing the country coverage and increasing measurement error. Thus, the human capital variable from PWT 8.0 is the one with widest coverage, and thus the only one that consistently allows for the use of heterogeneous panel data methods.

To investigate the use of returns to obtain the Mincerian-consistent measure of the PWT 8.0, we repeated the regressions in Tables 5–11 using two original alternative variables from Barro and Lee (2013), educational attainment above 15 and 25 years (which were linearly interpolated to obtain comparable series to the one used in the benchmark analysis). The results were consistent with previous ones, showing a statistically highly significant and positive effect of human capital on inequality for both variables in all specifications.

### Table 9

| Dependent variable: Gini measure | High-TFP sample | Low-TFP sample |
|----------------------------------|-----------------|----------------|
|                                  | (1)            | (2)            | (3)           | (4)           |
| **Gini net post-tax; post-transfer** |                |                |               |
| (/>SD)                           |                |                |               |
| **hcap**                        | 4.851***       | 4.687***       | -0.564        | 0.974         |
|                                  | (0.981)        | (0.974)        | (1.317)       | (1.374)       |
| **TFP**                         | -0.164         | -0.042         | 0.018         | -0.264*       |
|                                  | (0.173)        | (0.220)        | (0.127)       | (0.142)       |
| **Open**                        | -0.081         | -0.118         | -0.008        | -0.135        |
|                                  | (0.097)        | (0.081)        | (0.055)       | (0.094)       |
| No. of obs.                     | 1.629          | 1.463          | 1.671          | 1.130          |
| Avr. no. of obs.                | 38.8           | 41.8           | 27.4           | 34.2           |
| Min–max                         | 8–52           | 31–52          | 7–51           | 21–51          |
| No. of countries                | 42             | 35             | 61             | 33             |
| Wald                            | 26.05***       | 25.28***       | 0.22           | 6.03           |
| CD test (res)                   | –              | -1.04(0.298)   | –              | -1.24(0.214)   |
| Stat test (res)                 | –              | reject I(1)    | –              | reject I(1)    |

Notes: Dependent variables are natural logarithm of the Gini coefficients. All variables are in natural logarithms. hcap is human capital, TFP is total factor productivity and Open is openness ratio. A constant is included in all regressions but omitted from the table. Values in parentheses below coefficients are $P$-values from robust (clustered) standard errors. Level of significance: **$P<0.01$; * $P<0.1$. Wald test is a joint significance test for the regressors. CD test is a Pesaran (2004) cross-section dependence test on the null of cross-section independence carried out on the residuals from the regression ($P$-values in parentheses). Stat test is the Pesaran (2007) unit-root test carried out on the residuals. This test used 3 lags, and ‘rejects I(1)’ means that in all lags the test of unit root rejects. $/SD$ indicates that the Gini coefficient is divided by the source standard deviation to account for data uncertainty.
the tables above, we noted that despite the very high statistical significance (almost always with \( p \)-values less than 0.001), coefficients are slightly lower than those presented in the tables, oscillating between 1.3 and 2.6, indicating that a 1 per cent increase in years of schooling implies an increase in inequality from 1.3 per cent to 2.6 per cent. The remaining effect to those reported in the tables above should be attributed to differences in returns throughout the different levels of schooling. In order to investigate whether the interpolation approach would have eliminated the significance of our results, we ran regressions that eliminated the interpolated observations. This greatly decreased the number of observations available for each regression from nearly 3,200 observations to nearly 500 observations. Nevertheless, all regressions corresponding to specifications presented earlier in Table 11 maintain the highly significant positive signed human capital coefficient, with statistical significance of 5 per cent or less.

The human capital variable construction and the very robust results we have obtained give us confidence that the results obtained must be common to any correct measure of human capital, given that it has the wide time-series and cross-country coverage that this one does. As a consequence, our strong effect of human capital on inequality has non-negligible policy effects. Until now, and given the results in Barro (2000), the common wisdom has been that if some education increases inequality, it should be the higher levels of education. However, by construction, the measure of human capital employed strongly weights lower levels of education (due to higher returns for lower levels of education). Thus, the effect of education on inequality is particularly due to lower levels of education. This has policy relevance as politicians should be aware of this effect in promoting education, even at the lower levels. Nevertheless, this effect is absent from the poorer countries, which indicates no influence of

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**Table 10**

| Dependent variable: Gini measure | High-openness sample | Low-openness sample |
|----------------------------------|-----------------------|---------------------|
| Gini net post-tax; post-transfer | Gini net post-tax; post-transfer | Gini net post-tax; post-transfer | Gini net post-tax; post-transfer |
| (./SD) (>30, ./SD)               | (>30, ./SD)           | (>30, ./SD)         | (>30, ./SD)         |
| \( hcap \)                       | 3.34**                | 2.71**              | 2.174**             |
|                                  | (1.330)               | (1.374)             | (1.055)             |
| \( TFP \)                        | -0.098                | -0.042              | -0.074              |
|                                  | (0.227)               | (0.160)             | (0.252)             |
| \( Open \)                       | -0.006                | 0.028               | -0.069              |
|                                  | (0.076)               | (0.052)             | (0.073)             |
| No. of Obs.                      | 1,677                 | 1,623               | 1,297               |
| Avr. no. of obs.                 | 32.9                  | 31.2                | 37.1                |
| Min – max                       | 12 – 52               | 7 – 52              | 21 – 52             |
| No. of countries                 | 51                    | 52                  | 35                  |
| Wald                            | 6.5*                  | 4.61                | 4.86                |
| CD test (res)                    | –                     | 0.21 (0.833)        | –                   |
| Stat test (res)                  | –                     | reject I(1)         | –                   |
|                                 |                       |                     | reject I(1)         |

Notes: Dependent variables are natural logarithm of the Gini coefficients. All variables are in natural logarithms. \( hcap \) is human capital, TFP is total factor productivity and \( Open \) is openness ratio. A constant is included in all regressions but omitted from the table. Values in parentheses below coefficients are \( P \)-values from robust (clustered) standard errors. Level of significance: *** \( P \) < 0.01; ** \( P \) < 0.05; * \( P \) < 0.1. Wald test is a joint significance test for the regressors. CD test is a Pesaran (2004) cross-section dependence test on the null of cross-section independence carried out on the residuals from the regression (\( P \)-values in parentheses). Stat test is the Pesaran (2007) unit-root test carried out on the residuals. This test used 3 lags, and ‘rejects I(1)’ means that in all lags the test of unit root rejects. \( I/(SD) \) indicates that the Gini coefficient is divided by the source standard deviation to account for data uncertainty.

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18 Considering specifications in columns (1)–(4), as the time-series requirements of specifications in columns (5) and (6) are not met when considering only 5-year periods.
education in increasing inequality in those coun-
tries. Thus, generally, in poorer countries, policy
may enhance education with no caution about
rising inequality. In contrast, in rich countries,
improvements in education may call for redis-
tributive fiscal policy.

The second issue is related
to the correction of the Gini coefficient. We
addressed that by simply dividing the Gini
coefficient by the standard error, as explained
above. This standard error oscillates in the sample
from 0.0016 to 15.43, which gives an idea of the
difference in quality remaining in the data and
suggests the need to account for such quality
heterogeneity. In fact, 25 per cent of the obser-
vations present a standard error below 0.5.
Dividing the Gini coefficient by this standard
error would greatly magnify Gini coefficients in
the case of high precision (i.e. when standard
deviations approach zero). A correction that would
not possess that property is division of the Gini
coefficient by (1 plus the standard error).19 With
this, a high-precision Gini coefficient (with a
standard deviation close to 0) would not be increased,
although a low-precision coefficient would be
decreased.

The high significance of human capital
positive coefficients hardly changes with this
modification in the corrected Gini index in all the
different specifications we present in the paper
corresponding to specifications in Tables 5
columns (3) and (4)) and Tables 6–11). The only

| Dependent variable | Gini coefficient net income (/SD, >30) |
|--------------------|----------------------------------------|
| vars. only as CS avr. | Open | Open; TFP | Open; TFP; GDP p.c. | Open; without TFP | TFP | Open; TFP |
| lags of CS Avr. | 0 | 0 | 0 | 0 | 3 (TFP); 4 (other) | 3 (TFP, Open); 4 (other) |
| hcap | 3.801*** (0.000) | 3.854*** (0.000) | 1.984*** (0.001) | 3.716*** (0.000) | 3.312** (0.026) | 2.974* (0.075) |
| TFP | -0.204 (0.248) | - | - | - | - | - |
| No. of obs. | 2,593 | 2,855 | 2,855 | 2,855 | 2,383 | 2,240 |
| Avr. no. of obs. | 38.1 | 38.6 | 38.6 | 38.6 | 32.2 | 33.9 |
| Min–max | 21–52 | 21–52 | 21–52 | 21–52 | 17–48 | 24–48 |
| No. of countries | 68 | 74 | 74 | 74 | 74 | 66 |
| Wald | 78.80*** (0.839) | 97.11*** (0.420) | 75.50*** (0.314) | 133.90*** (0.058) | 49.13*** (0.261) | 36.07*** (0.602) |
| CD test (res) | -0.20 | 0.81 | -1.01 | 1.89* | 1.12 | 0.52 |
| Stat test (res) | Reject I(1) | Reject I(1) | Reject I(1) | Reject I(1) | Reject I(1) | Reject I(1) |
| sig. signs/countries for hcap | /\(37) \(\backslash(2) | /\(44) \(\backslash(6) | /\(22) \(\backslash(9) | /\(42) \(\backslash(8) | /\(13) \(\backslash(9) | /\(14) \(\backslash(6) |
| sig. signs/countries for TFP | /\(12) \(\backslash(15) | - | - | - | - | - |

Notes: Dependent variables are natural logarithm of the Gini coefficients. All variables are in natural logarithms. hcap is human
capital, TFP is total factor productivity and Open is openness ratio. A constant is included in all regressions but omitted from the
table. Values in parentheses below coefficients are P-values from robust (clustered) standard errors. Level of significance:
*** P<0.01; ** P<0.05; * P<0.1. Wald test is a joint significance test for the regressors. CD test is a Pesaran (2004) cross-section
dependence test on the null of cross-section independence carried out on the residuals from the regression (P-values in parentheses).
Stat test is the Pesaran (2007) unit-root test carried out on the residuals. This test used 3 lags, and ‘rejects I(1)’ means that in all lags
the test of unit root rejects. sig. signs/countries for hcap, TFP or Open gives the number of countries with positive or negative
statistical significant coefficient. (/SD) indicates that the Gini coefficient is divided by the source standard deviation to account for
data uncertainty. The list of countries that enter into columns (3) and (4) is presented in Appendix B.

19 The alternative proposed uncertainty-corrected measure is thus \(GINI/(1+sd(GINI))\), where \(GINI\) is the
Gini index provided by SWIID and \(sd(GINI)\) is the standard deviation of the Gini index, also provided by
the SWIID and which corrects for uncertainty or measurement error within the sources. Results are
provided in Appendix C.

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expected difference in results is quantitative (see Tables C.1–C.3 in the Appendix). 20 With this alternative variable, a 1 per cent increase in human capital would increase inequality by 0.62–1.52 per cent (compared to 1.98–3.85 per cent with the baseline measure). The causal relationship between human capital and inequality in regressions corresponding to specifications in Table 11, but in which all the cross-sections (and not restricted to the ones with larger time series) are included, is also robust to the mentioned change in the definition of the corrected Gini coefficient. The original variables from Barro and Lee (2013), for educational attainment above 15 and 25 years, also present a robust influence in inequality if the measure of inequality changes according to the described above (i.e. dividing the Gini coefficient by (1 plus the standard error)).

V Conclusion

There is scant empirical literature on the determinants of inequality. We contribute to that literature by evaluating potential determinants of inequality in a large panel dataset of countries. Earlier attempts have faced problems with the coverage and quality of the income inequality data. We use a recent standardised measure of the Gini coefficient, due to Solt (2009), to evaluate human capital, TFP and openness as possible determinants of inequality. We conclude that this measure also needs to be corrected for differences in original data precision. Failure to do so would determine crucially different and misleading results concerning the influence of human capital on inequality. Fortunately, Solt (2009) also provides the means to implement such correction.

We adopted empirical specifications allowing for heterogeneity in the long-run relationship between human capital, TFP, openness and inequality across countries, reflecting a rich theoretical literature on the issue. This heterogeneity in specifications extends to the unobservable determinants of inequality and its determinants (e.g. human capital), which we addressed by means of a flexible common factor model framework. Our is the first panel study on the determinants of inequality to address parameter heterogeneity and cross-country dependence.

We found a positive statistically significant effect of human capital on inequality once the Gini coefficient is corrected for differences in its precision. This result is robust to several specification changes both in the inequality variable and in the human capital variable. Notably, the positive effect of human capital on inequality remains highly significant in methods robust to reverse causality. Contrary to what may have been the current wisdom until now, it is not only tertiary education that tends to cause higher inequality, but the effect is highlighted with a measure that strongly weights lower levels of education, suggesting further research on the effect of primary education on inequality. No statistical significant results were obtained for the effect of TFP and openness when considering the whole sample, despite a few negative effects of TFP on inequality emerging in some sub-samples of countries. These results suggest that theories that are not based on country heterogeneity to explain the relationship between technology, openness, and inequality may be unrealistic. In fact, institutions and history may be behind the heterogeneous effects of human capital, technology, and openness on inequality detected. Additionally, contrary to most of the earlier evidence, the results in this paper suggest that human capital may be seen as the most important worldwide determinant of inequality, giving credit to the skill-biased technical change or the general-purpose technology theories, which predict a rise in inequality in consequence of the rise in human capital. Although we found positive effects of all levels of human capital, curiously the strongest effect come from primary schooling. Also consistent with theories, this effect is not present in poor countries. These results are also important for policy: cautious about the effects of education on inequality maybe calling for redistributive fiscal policies should be taken only on rich countries.

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Appendix A

Additional Unit-Root and Cointegration Tests

| Variable       | Lag | Gini net income SWIID (>30) | Gini net income SWIID (>30, /SD) | Human capital | TFP | Openness |
|----------------|-----|-----------------------------|----------------------------------|---------------|-----|----------|
| Pesaran (2007) Test without Trend |     |                             |                                  |               |     |          |
| Zt stat.       | 0   | -19.818***                  | -32.761***                       | -0.893        | -41.383*** | -54.611*** |
| P-value        |     | (0.000)                     | (0.000)                          | (0.186)       | (0.000) | (0.000)  |
| Zt stat.       | 1   | -9.705***                   | -26.800***                       | -2.299**      | -26.245*** | -45.136*** |
| P-value        |     | (0.000)                     | (0.000)                          | (0.011)       | (0.000) | (0.000)  |
| Zt stat.       | 2   | -12.056***                  | -16.646***                       | -3.550***     | -18.507*** | -30.995*** |
| P-value        |     | (0.000)                     | (0.000)                          | (0.000)       | (0.000) | (0.000)  |
| Zt stat.       | 3   | -8.450***                   | -12.134***                       | -5.837***     | -13.252*** | -23.578*** |
| P-value        |     | (0.000)                     | (0.000)                          | (0.000)       | (0.000) | (0.000)  |
| Pesaran (2007) Test with Trend |     |                             |                                  |               |     |          |
| Zt stat.       | 0   | -18.382***                  | -30.603***                       | 2.477         | -40.184*** | -53.027*** |
| P-value        |     | (0.000)                     | (0.000)                          | (0.993)       | (0.000) | (0.000)  |
| Zt stat.       | 1   | -6.394***                   | -23.520***                       | 1.140         | -23.809*** | -41.989*** |
| P-value        |     | (0.000)                     | (0.000)                          | (0.873)       | (0.000) | (0.000)  |
| Zt stat.       | 2   | -9.161***                   | -12.366***                       | -0.112        | -15.671*** | -26.970*** |
| P-value        |     | (0.000)                     | (0.000)                          | (0.455)       | (0.000) | (0.000)  |
| Zt stat.       | 3   | -7.046***                   | -8.002***                        | -2.620***     | -10.564*** | -19.422*** |
| P-value        |     | (0.000)                     | (0.000)                          | (0.004)       | (0.000) | (0.000)  |

Notes: All variables are in natural logarithms. >30 indicates that only cross-sections with more than 30 time-series observations are included. /SD indicates that the Gini coefficient is divided by the source standard deviation to account for data uncertainty. Level of significance: ***P<0.01; ** P<0.05; * P<0.1.
### TABLE A2
**Cointegration Tests**

| (1) | (5) | (6) | (7) | (8) |
|-----|-----|-----|-----|-----|
| Lag Trend Gt test Ga test Pt test Pa test |
| Dependent variable | Gini coefficient net income (>30) (from SIIWD) | P-value | 1 | No/C0 |
|                      | -2.649*** | (0.000) | (0.767) | (0.000) | (0.000) |
|                      | -6.297 | (0.000) | (0.982) | (0.000) | (0.001) |
|                      | -13.782*** | (0.000) | (0.740) | (0.000) | (0.036) |
|                      | -8.885*** | (0.000) | (0.996) | (0.000) | (0.557) |
| P-value | 1 | Yes/C0 |
|                      | -3.567*** | (0.000) | (0.996) | (0.000) | (0.001) |
|                      | -8.984 | (0.000) | (0.982) | (0.000) | (0.001) |
|                      | -15.144*** | (0.000) | (0.740) | (0.000) | (0.036) |
|                      | -13.135*** | (0.000) | (0.996) | (0.000) | (0.001) |
| P-value | 2 | No/C0 |
|                      | -2.745*** | (0.000) | (0.996) | (0.000) | (0.036) |
|                      | -6.394 | (0.000) | (0.982) | (0.000) | (0.001) |
|                      | -10.735*** | (0.000) | (0.740) | (0.000) | (0.036) |
|                      | -5.930** | (0.000) | (0.982) | (0.000) | (0.001) |
| P-value | 2 | Yes/C0 |
|                      | -3.201*** | (0.000) | (0.996) | (0.000) | (0.001) |
|                      | -8.194 | (0.000) | (0.982) | (0.000) | (0.001) |
|                      | -12.938*** | (0.000) | (0.996) | (0.000) | (0.001) |
|                      | -8.745 | (0.000) | (0.996) | (0.000) | (0.001) |
| Dependent variable | Human capital (from PWT 8.0) | P-value | 1 | No/C0 |
|                      | -2.037* | (0.088) | (0.996) | (0.038) | (0.979) |
|                      | -4.068 | (0.000) | (0.996) | (0.000) | (0.000) |
|                      | -8.556** | (0.000) | (0.996) | (0.000) | (0.000) |
|                      | -2.302 | (0.000) | (0.996) | (0.000) | (0.000) |
| P-value | 1 | Yes/C0 |
|                      | -1.964 | (0.990) | (0.996) | (0.849) | (0.976) |
|                      | -8.196 | (0.000) | (0.996) | (0.000) | (0.000) |
|                      | -9.005 | (0.000) | (0.996) | (0.000) | (0.000) |
|                      | -6.354 | (0.000) | (0.996) | (0.000) | (0.000) |
| P-value | 2 | No/C0 |
|                      | -2.096** | (0.048) | (0.998) | (0.442) | (0.992) |
|                      | -3.763 | (0.000) | (0.998) | (0.000) | (0.000) |
|                      | -6.934 | (0.000) | (0.998) | (0.000) | (0.000) |
|                      | -1.961 | (0.000) | (0.998) | (0.000) | (0.000) |
| P-value | 2 | Yes/C0 |
|                      | -1.797 | (1.000) | (0.999) | (0.976) | (0.987) |
|                      | -7.665 | (0.000) | (0.999) | (0.000) | (0.000) |
|                      | -8.186 | (0.000) | (0.999) | (0.000) | (0.000) |
|                      | -6.024 | (0.000) | (0.999) | (0.000) | (0.000) |
| Notes: All variables are in natural logarithms. >30 indicates that only cross-sections with more than 30 time-series observations are included. All tests include a constant. Level of significance: *** \( P < 0.01 \); ** \( P < 0.05 \); * \( P < 0.1 \). Rejection of \( H_0 \) in Ga and Gt tests should be taken as evidence of cointegration of at least one of the cross-sectional units. Rejection of \( H_0 \) in Pa and Pt tests should therefore be taken as evidence of cointegration for the panel as a whole. |

### Appendix B

**Lists of Countries**

This section lists the countries used in the main regressions in the paper

**B1. Sample in Tables 5, column (3)**

Argentina, Armenia, Australia, Austria, Barbados, Belgium, Bolivia, Botswana, Brazil, Bulgaria, Burundi, Cameroon, Canada, Central African Republic, Chile, China, Colombia, Costa Rica, Côte d’Ivoire, Croatia, Cyprus, Czech Republic, Denmark, Dominican Republic, Ecuador, Egypt, Estonia, Fiji, Finland, France, Germany, Greece, Guatemala, Honduras, Hong Kong, Hungary, Iceland, India, Indonesia, Iran, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Republic of Korea, Kyrgyz Republic, Latvia, Lesotho, Lithuania, Luxembourg, Malaysia, Malta, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Morocco, Mozambique, Namibia, Netherland, New Zealand, Niger, Norway, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Romania, Russian Federation, Rwanda, Senegal, Serbia, Sierra Leone, Singapore, Slovak Republic, Slovenia, South Africa, Spain, Sri Lanka, Swaziland, Sweden, Switzerland, Taiwan, Tajikistan, Tanzania, Thailand, Togo, Trinidad and Tobago, Tunisia, Turkey, Ukraine, United Kingdom, United States, Uruguay, Venezuela, Zimbabwe.

**B2. Sample in Tables 5, column (4), and Table 8, column (1)**

Argentina, Australia, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Côte d’Ivoire, Denmark, Egypt, Estonia, Fiji, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Iran, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Republic of Korea, Kyrgyz Republic, Latvia, Lithuania, Malaysia, Mauritius, Mexico, Moldova, Morocco, Mozambique, Namibia, Netherlands, New Zealand, Norway, Panama, Peru, Philippines, Poland, Portugal, Russian Federation, Sierra Leone, Singapore, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Tanzania, Thailand, Trinidad and Tobago, Tunisia, Turkey, Ukraine, United Kingdom, United States, Uruguay, Venezuela.
B3. Sample in Tables 11, columns (2), (3), (4) and (5)
Argentina, Australia, Bangladesh, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Côte d’Ivoire, Denmark, Egypt, El Salvador, Estonia, Fiji, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Iran, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Republic of Korea, Kyrgyz Republic, Latvia, Lithuania, Malawi, Malaysia, Mauritius, Mexico, Moldova, Morocco, Nepal, Netherlands, New Zealand, Norway, Pakistan, Panama, Peru, Philippines, Poland, Portugal, Russian Federation, Sierra Leone, Singapore, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Tanzania, Thailand, Trinidad and Tobago, Tunisia, Turkey, Ukraine, United Kingdom, United States, Uruguay, Venezuela, Zambia.

B4. Sample in Tables 11, column (6)
Argentina, Australia, Bangladesh, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Côte d’Ivoire, Denmark, Egypt, El Salvador, Fiji, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Iran, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kenya, Republic of Korea, Malawi, Malaysia, Mauritius, Mexico, Morocco, Nepal, Netherlands, New Zealand, Norway, Pakistan, Panama, Peru, Philippines, Poland, Portugal, Sierra Leone, Singapore, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Taiwan, Tanzania, Thailand, Trinidad and Tobago, Tunisia, Turkey, United Kingdom, United States, Uruguay, Venezuela, Zambia.

Appendix C
Alternative Corrected Gini index

TABLE C1
Inequality, Human Capital, TFP, and Openness

|               | (1)                        | (2)                        |
|---------------|----------------------------|----------------------------|
| Dependent variable: | Gini net post-tax; post-transfer./(1+SD) | Gini net post-tax; post-transfer ./(1+SD), >30 |
| hcap          | 1.10***                    | 1.44***                    |
|               | (.004)                     | (.000)                     |
| TFP           | .006                       | -0.058                     |
|               | (.931)                     | (0.498)                    |
| Open          | .02                        | 0.02                       |
|               | (.460)                     | (0.461)                    |
| No. of obs.   | 3,300                      | 2,593                      |
| Avr. no. of obs. | 32                    | 38.1                       |
| Min–max       | 7–52                       | 21–52                      |
| No. of countries | 103                   | 68                        |
| Wald          | 9.01**                     | 15.39***                   |
| CD test (res) | –                          | 1.10 (0.272)               |
| Stat test (res) | –                        | rejects I(1)               |
| sig. signs /countries for hcap | /\(38)/\(12) | /\(31)/\(4)               |
| sig. signs /countries for TFP | /\(19)/\(19) | /\(11)/\(16)               |
| sig. signs /countries for Open | /\(17)/\(5) | /\(15)/\(4)               |

Notes: Dependent variables natural logarithm of the Gini coefficients. All variables are in natural logarithms. A constant is included in the regressions but omitted from the table. Values in parentheses below coefficients are \(P\)-values from robust (clustered) standard errors. Level of significance: *** \(P<0.01\); ** \(P<0.05\); * \(P<0.1\). Wald test is a joint significance test for the regressors. CD test is a Pesaran (2004) cross-section dependence test on the null of cross-section independence carried out on the residuals from the regression \(P\)-value in parentheses). Stat test is the Pesaran (2007) unit-root test carried out on the residuals. This test used 3 lags, and ‘rejects I(1)’ means that in all lags the test of unit root rejects. The lists of countries that enter in columns (3) and (4) are provided in Appendix B. \(/
(1+SD) indicates that the Gini coefficient is divided by 1 plus the source standard deviation to account for data uncertainty.

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|               | Rich sample |             | Poor sample |             |
|---------------|-------------|-------------|-------------|-------------|
|               | (1)         | (2)         | (3)         | (4)         |
| dependent variable:                              |             |             |             |             |
| Gini measure |             |             |             |             |
| hcap         | 1.49***     | 1.29***     | 0.76        | 0.499       |
|              | (0.003)     | (0.004)     | (0.170)     | (0.451)     |
| TFP          | 0.02        | −0.03       | −0.046      | −0.097      |
|              | (0.853)     | (0.792)     | (0.563)     | (0.396)     |
| Open         | 0.01        | −0.04       | 0.024       | −0.016      |
|              | (0.777)     | (0.534)     | (0.395)     | (0.712)     |
| No. of obs.  | 1.657       | 1.431       | 1.643       | 1.162       |
| Avr. no. of obs. | 36.8 | 40.9 | 28.3 | 35.2 |
| Min–max      | 12–52       | 22–52       | 7–48        | 21–48       |
| No. of countries | 45  | 35  | 58  | 33  |
| Wald         | 9.22***     | 8.62**      | 2.94        | 1.43        |
|              | (0.307)     |             |             |             |
| CD test (res)| –           | 1.02        | –           | −0.06(0.955) |
| Stat test (res)| – | reject I(1) | – | reject I(1) |

Notes: Dependent variables natural logarithm of the Gini coefficients. All variables are in natural logarithms. A constant is included in the regressions but omitted from the table. Values in parentheses below coefficients are P-values from robust (clustered) standard errors. Level of significance: ***$P<0.01$; **$P<0.05$; *$P<0.1$. Wald test is a joint significance test for the regressors. CD test is a Pesaran (2004) cross-section dependence test on the null of cross-section independence carried out on the residuals from the regression ($P$-value in parentheses). Stat test is the Pesaran (2007) unit-root test carried out on the residuals. This test used 3 lags, and ‘rejects I(1)’ means that in all lags the test of unit root rejects. The lists of countries that enter in columns (3) and (4) are provided in Appendix B. $/(1+SD)$ indicates that the Gini coefficient is divided by 1 plus the source standard deviation to account for data uncertainty.
### Table C3

**Inequality, Human Capital, TFP, and Openness (Robustness)**

| Dependent variable | Gini coefficient net income (\(1/(1+SD)\), >30) |
|--------------------|-------------------------------------------------|
| **Vars. only as CS avr.** | Open | Open; TFP | Open; TFP; GDP p.c. | Open; without TFP | Open; TFP | Open; TFP |
| Lags of CS Avr. | 0 | 0 | 0 | 0 | 2 (Gini); 3 (hcp); 0 (other) | 3 (all) |
| **hcp** | 1.31*** (0.001) | 1.54*** (0.000) | 0.62** (0.035) | 1.52*** (0.000) | 1.10** (0.028) | 2.23*** (0.009) |
| **TFP** | –0.064 (0.441) | – | – | – | – | – |
| No. of obs. | 2,593 | 2,855 | 2,855 | 2,855 | 2,463 | 2,445 |
| Avr. no. of obs. | 38.1 | 38.6 | 38.6 | 38.6 | 33.3 | 33.5 |
| Min – max | 21–52 | 21–52 | 21–52 | 21–52 | 18–49 | 19–49 |
| No. of countries | 68 | 74 | 74 | 74 | 74 | 73 |
| Wald | 55.98*** (0.250) | 68.92*** (0.254) | 34.68*** (0.834) | 34.68*** (0.694) | 43.10*** (0.000) | 24.65* (0.000) |
| CD test (res) | 1.15 | 1.14 | 0.21 | 0.39 | 3.72*** (0.000) | 6.41*** (0.000) |
| Stat test (res) | Reject I(1) | Reject I(1) | Reject I(1) | Reject I(1) | Reject I(1) | Reject I(1) |
| sig. signs /countries for hcap | \((13)\)\((3)\) | \((41)\)\((9)\) | \((19)\)\((8)\) | \((42)\)\((9)\) | \((14)\)\((9)\) | \((16)\)\((11)\) |
| sig. signs /countries for TFP | – | – | – | – | – | – |

**Notes:** Dependent variables natural logarithm of the Gini coefficients. All variables are in natural logarithms. A constant is included in the regressions but omitted from the table. Values in parentheses below coefficients are \(P\)-values from robust (clustered) standard errors. Level of significance: *** \(P<0.01\); ** \(P<0.05\); * \(P<0.1\). Wald test is a joint significance test for the regressors. CD test is a Pesaran (2004) cross-section dependence test on the null of cross-section independence carried out on the residuals from the regression (\(P\)-value in parentheses). Stat test is the Pesaran (2007) unit-root test carried out on the residuals. This test used 3 lags, and 'rejects I(1)' means that in all lags the test of unit root rejects. The lists of countries that enter in columns (3) and (4) are provided in Appendix B. Vars. only as CS Avr. means variables that only enter regression as cross-section average but not as country-specific variable. \(1/(1+SD)\) indicates that the Gini coefficient is divided by 1 plus the source standard deviation to account for data uncertainty.