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National Income and Its Distribution

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Abstract

Does the distribution of income within a country become more equal as it grows richer? This paper uses plausibly exogenous variations in trade-weighted world income and international oil price shocks as instruments for within-country variations in countries' real GDP per capita to examine this issue for a large sample of advanced and developing countries. Our findings indicate that increases in national income have a significant moderating effect on income inequality: a one percent increase in real GDP per capita, on average, reduces the Gini coefficient by around 0.08 percentage points, a result that is robust across income levels, different time horizons, and alternative estimation techniques. From a policy perspective, our results suggest that education policies that promote equity and help individuals continue on to higher levels of education could help reduce income inequality.

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I. INTRODUCTION

Whether or not countries' distribution of income becomes more equal as they grow richer is an important question in both academic and policy debates. This is because inequality can be a signal of income mobility and opportunity as much as it is a signal of injustice—a reflection of persistent disadvantage for particular segments of society. A large body of work since the 1950s has focused on the evolution of income inequality in the course of economic development. Indeed, Simon Kuznets' query in his 1954 Presidential Address to the American Economic Association was: "Does inequality in the distribution of income increase or decrease in the course of a country's economic growth?" Kuznets' own exploration led to the inverted U hypothesis—the notion that inequality first increases and then decreases as economies grow.

This paper aims to revisit these issues. Is income inequality reduced in the context of economic growth? Does this relationship depend on the country's level of economic development? Are there non-linearities in this relationship, with inequality first increasing and then declining as economies develop? What is the key policy channel through which the inequality-reducing effect of income growth materializes? Answers to these questions have important macroeconomic implications, especially as high levels of inequality can coalesce political power and economic opportunities in the hands of a few at the expense of the majority, lead to a waste of human resources and potential, cause investment-reducing political and economic instability, and fuel crisis risk (Dabla-Norris, 2012).

Whereas initial studies of the growth-inequality nexus have either focused on time series for individual countries, or explored this issue in a cross-sectional context, newly compiled inequality data since the 1990s allows for the use of panel regressions that enable a focus on within-country variation in inequality. While an important step forward, potential growth-inequality correlations are still left open to interpretation. In particular, one possibility is reverse causality, whereby inequality drives growth outcomes. Indeed, there exists a large extant literature emphasizing this very link. Additionally, there is a possibility that omitted variables that affect both income growth and its distribution are not appropriately accounted for in the empirical specification. These concerns imply the need for an exogenous source of variation in national income to examine its impact on inequality.

In this paper we employ two instrumental variables (IVs) to examine the growth-inequality nexus over five-year horizons (panel regressions) for a large sample of advanced and developing economies, spanning 1960–2007. The first IV is oil price shocks (OPS), defined as the interaction between the change in the international oil price and countries' average oil net-export GDP shares. As shown previously (see, for e.g., Brueckner et al., 2012a, b), this variable is a strong instrument for income changes, and also extracts a very persistent component of national income.[1] Another complementary IV is trade-weighted world income (TWWI), the weighted sum of world income for each country, with time-invariant weights varying across countries depending on their trade patterns. An advantage of our approach is that it allows us to disentangle the precise source of income growth driving the estimated growth-inequality relationship. Our principal findings can be summarized as follows:

First, *on average, economic growth reduces income inequality*. We find that a one percent increase in GDP per capita reduces the Gini coefficient by around 0.08 percentage points. For example, a country like Malaysia, with a (sample average) Gini coefficient of 0.46 and (sample average) PPP GDP per capita of $5174, would expect to see its Gini coefficient decline to 0.38 as its income per capita doubles. Further, we find that income growth boosts the relative income share of the lower quintile and the middle-class and results in a decline in the income share accruing to the top quintile. Increases in income are also associated with a significant decrease in the poverty gap and headcount ratios. While our results are consistent with Dollar and Kraay (2002) and Dollar et al., (2013) in reinforcing their conclusion that the poor benefit from growth, our findings, in fact, suggest that the poor and the middle-class stand to benefit proportionately more than the rich.

Second, *our results appear to hold intact against a battery of robustness checks*. These include alternative estimation techniques, different time periods and horizons, checking for sensitivity to outliers, and alternative data sources. All these tests contribute to making us confident that the empirical results are indeed robust and capture the causality from national income to inequality.

Third, *we find no support for a Kuznets curve*. The empirical validity of the Kuznets curve has been intensively investigated in a wide variety of settings, but the evidence hitherto has been inconclusive. Using internally consistent time series of inequality for a large number of countries, we find that within-country income inequality declines as the country develops.

Fourth, *the inequality reducing effect of income growth holds for countries at different stages of development and across regions.* Our results indicate that while low levels of economic development and a high share of rural and agricultural populations, weaken the inequality reducing effect of income growth, this difference is not significant in statistical terms. Further, although the inequality reducing effects of income growth are significantly smaller in Latin American and Asian countries, with growth leading to smaller income gains for the lower quintiles, they are still significantly different from zero. This implies that, on average, within-country inequality in these regions has still fallen with income growth, albeit by less than in other regions.

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[1] A potential limitation of this IV is that it captures national income changes that are due to windfalls (or income losses) arising from oil price fluctuations. While important, this conceivably only extracts a portion of exogenous variation in national income.

Fifth, *education policies matter*. Galor and Zeira (1993) show that, in the presence of credit market imperfections and indivisibilities in human capital investment, increases in aggregate income are associated with lower inequality.[2] Their model suggests that education is a key channel through which the inequality-reducing effect of income growth materializes. Motivated by this, we find that including education as a control variable substantially reduces the coefficient on national income.[3] We also find that increases in income have a significant positive effect on educational attainment. Our findings further suggest that education, rather than government expenditures per se or financial sector development, is the most important channel for mediating the income growth-inequality relationship.

The rest of the paper proceeds as follows. The next section provides a brief review of the related literature. Section III describes the data and discusses the estimation framework. Section IV presents the main empirical findings and robustness analysis. Section V discusses the role of economic development. Section VI examines the policy channels mediating the growth-inequality nexus; Section VII concludes.

II. Literature Review

Sustained income growth can affect inequality through a variety of channels (see Jaumotte et al., 2013, for a more in-depth analysis of the transmission channels). One such channel is technological and structural change. To the extent that income growth is driven by technological progress, depending on whether it is skill-biased or not, inequality could either increase or decline. Globalization may also widen inequality. For instance, off-shoring could make labor demand more skill intensive in both poorer and richer countries, thus increasing inequality in both groups of countries (Feenstra and Hanson, 1996). Moreover, trade may increase labor income inequality by lowering employment or the relative earnings of low-income workers (Helpman et al., 2010). An additional channel is that of increased state capacity following income windfalls. This may result due to an enhanced capacity of governments to enforce laws and regulations, raise tax revenues to this end, and put in place effective public education and social insurance systems, thus affecting the distribution of income.

Early work on the inequality-growth relationship was largely carried out in the context of cross-country regressions. This work, exemplified by Ahluwalia (1976a, 1976b), Anand and Kanbur (1993), Milanovic (2000) and Paukert (1973), found an inverted U-shaped relationship between income and inequality, suggesting that inequality peaked for middle-income countries. While there was a tendency to interpret this relationship in causal terms, subsequent work, incorporating country fixed effects in the context of panel cross-country

[2] Other models such as Banerjee and Newman (1993) and Greenwood and Jovanovic (1990) also suggest that credit market imperfections play an important role in shaping income inequality.

[3] See Brueckner and Gradstein (2013) for an analysis of the causal effect of income on education.

analysis, failed to detect any significant non-linear effects of income growth on inequality (see for e.g., Deininger and Squire, 1998; Easterly, 1999; Fields, 2001).

Dollar and Kraay (2002) and Kraay (2006) argued that economic growth reduces poverty—growth tends to increase the income of the bottom quintile by as much as that of the average income in the population.[4] It should be emphasized, however, that while these studies employ country fixed effects, changes in national income are typically not instrumented for, opening up the possibility for a number of alternative interpretations. Dollar and Kraay (2002) and Lundberg and Squire (2003) are important early attempts to account for endogeneity bias, albeit using different variables as instruments from those employed in this paper.

There is also a growing body of work that focuses on the reverse causality from inequality to growth.[5] In particular, early work, by Barro (2000) and Forbes (2000) generated somewhat inconclusive results: the former finding a non-monotonic effect, while the latter highlighting a positive effect. Galor et al., (2009) argue both theoretically and empirically that (land) inequality subverts growth by inhibiting the willingness of politically powerful population groups to invest in human capital formation. Likewise, Easterly (2007), using geography rooted IVs, finds that inequality causes underdevelopment. Halter et al., (2013) suggest that the effect of inequality on growth depends on the time span explored. Ostry et al., (2011) document the effects of inequality on growth as well as spell duration.

While the precise nature of the various channels through which inequality affects growth remains a matter of debate, the above literature implies that reverse causality is a serious concern when examining the evolution of inequality in the course of economic development. This, in turn, reinforces the need for carefully designed identification methods.

III. Data and Model

A. Data Description

We work with a large cross-country dataset of high-quality, survey-based measures of average incomes and income distributions. Our primary data source is the UN-WIDER World Income Inequality Database (WIID, 2008), where the data was filtered to drop low-quality observations. This was supplemented with data from the World Bank's POVCALNET database for developing countries. To ensure comparability between the two data sources, we make adjustments to the data sets for individual countries so that income shares consistently correspond to those of a consumption (or an income) survey. This leaves

[4] Dollar et al. (2013) update and extend this work to argue that the poorest 40 percent benefit from economic growth. Pinkovskiy and Sala-i-Martin (2013) find that economic growth has reduced inequality in Africa.

[5] This work is rooted in classical writings (Kaldor, 1955), but has been reinvigorated by neoclassical economists. See Galor (2011a,b) for an extensive review of the theoretical and empirical aspects of this relationship.

us with a total of 3319 survey-years for 154 countries spanning 1960–2007. We identify and drop duplicates and eliminate duplicate survey-years with inferior quality data from the WIID, survey-years for which no extra information (consumption/income) is available; and survey-years for which the income shares add up to less than 99 or more than 101. This leaves us with 2785 survey-years for 144 countries. We next aggregate the inequality data to the 5-year level by taking a simple average of the observed annual observations over five years. In the regression analysis, the focus is on countries for which inequality data are available for at least two or more consecutive 5-year intervals.

Two main measures are employed to capture income inequality. The first is the Gini coefficient, which measures the extent to which the distribution of income among individuals or households within an economy deviates from a perfectly equal distribution. The second measure is the share of income held by the first, second, third, fourth, and fifth quintile. While the former is an aggregate measure, it may mask detailed patterns of differences across income levels (i.e., the share that accrues to subgroups of the population). As discussed in Atkinson et al., (2011), this distinction can be important for assessing within-country inequality.

We employ two instruments to examine the relationship between national income and inequality. The first instrument is oil price shocks (OPS), data for which is taken from Brueckner et al., (2012). The oil price shock variable is constructed as $\text{OPS}_{ct} = \Delta\ln(\text{OilPrice})_t * \theta_c$. This variable takes into account the fact that changes in the international oil price have a larger impact on countries that are highly dependent on oil exports (imports) by weighting the oil price by the average (i.e., time-invariant) share of net oil exports in GDP (θc). The second instrument is trade-weighted world income (TWWI). Data on trade-weighted world income are from Acemoglu et al., (2008). Countries' trade-weighted world income, TWWI, is constructed as $TWWI_{it} = \sum_{j \neq i} w_{ij} GDP_{jt}$, where w_{ij} is the share of trade between country i and country j in the GDP of country i (measured using trade shares between 1980 and 1989 to maximize coverage). Note that this variable takes into account the fact that shocks to trading partners' GDP have larger effects on country i's GDP the larger are bilateral trade relations between country i and country j, and the more open country i is to international trade.

Data on real GDP per capita are taken from the Penn World Table (Heston et al., 2012). Given the availability of data on inequality, PPP GDP per capita, the oil price instrument, and the trade-weighted world income instrument, the largest possible 5-year non-overlapping sample comprises a total of 80 countries.

We consider a number of potential variables mediating the relationship between income and inequality, including education, financial sector development, and government spending. Data on the average years of education in the population aged 15 and above are taken from Barro and Lee (2010). We also obtain data on the share of the population with completed secondary school from Barro and Lee (2010). Financial sector development is proxied by the ratio of domestic credit to the private sector over GDP, from the WDI (2013). Data on the

GDP share of government consumption expenditures are from the Penn World Table (Heston et al., 2012).

B. Estimation Framework

Our baseline regression relates income inequality to the log of real GDP per capita:

(1) $$\text{Inequality}_{it} = \alpha_i + \beta_t + \eta \ln(\text{GDP p.c.})_{it} + u_{it}$$

where α_i are country fixed effects that control for cross-country differences in geography, history, ethnicity and other time-invariant determinants of income and its distribution. The year fixed effects, β_t, capture common time shocks affecting both GDP per capita and the distribution of income within countries (e.g., common shocks to economic growth due to changes in the world business cycle or political events, such as the end of the Cold War). We use the level of GDP per capita as the main explanatory variable because in the country fixed effects specification this is tantamount to asking the question: what happens to the within-country distribution of income as the log of national income changes (i.e., as the country develops). This levels specification was also employed in previous literature (e.g., Dollar and Kraay, 2002).

Following the empirical growth literature, we estimate equation (1) using 5-year non-overlapping panel data. The sample period is 1960-2007 and covers 80 countries. See Appendix Table 1 for descriptive statistics and Appendix Table 2 for the list of countries in our sample.

An important issue in the estimation of equation (1) is the endogeneity of countries' GDP per capita. To correct for endogeneity biases, we use two-stage least squares (2SLS) estimation. The corresponding first-stage equation is:

(2) $$\ln(\text{GDPp.c.})_{it} = a_i + b_t + c\ln(\text{TWWI})_{it} + \text{dOPS}_{it} + e_{it}$$

The assumption (exclusion restriction) in the 2SLS estimation is that trade-weighted world income and oil price shocks only affect income inequality through their effect on GDP per capita. We discuss this exclusion restriction in detail below.

IV. Empirical Results

A. Baseline Results

Figures 1 and 2 present simple correlations of the relationship between national income and income inequality. The graphs indicate that there is a negative relationship between the two, with the share of the bottom quintile increasing and that of the upper quintile decreasing with income. Note, however, that these observations pertain to raw cross-country correlations. As a step toward more rigorous causality analysis, Table 1 presents our baseline estimates, with Panel A reporting the results of the 2SLS estimation, and Panel B documenting the LS estimates. All regressions include country and time fixed effects. In column (1) we report estimates with the Gini coefficient as the dependent variable. In columns (2)–(6) the dependent variables are the income shares accruing to the 1st -5th quintiles.

The main result from the 2SLS estimation (Panel A) is that exogenous within-country variations in GDP per capita are negatively and significantly related to within-country variations in income inequality (Table 2).[6] For example, the economic interpretation of the estimated coefficient on log GDP per capita of -8.5 in column (1) is that, on average, a one percent (0.01 log point) increase in GDP per capita leads to a reduction in the Gini coefficient of over 0.08 percentage points. For example, a country like the Philippines, with a (sample average) Gini coefficient of 0.43 and (sample average) PPP GDP per capita of $2769, would expect to see its Gini coefficient decline to 0.35 as its income per capita doubles. Another noteworthy result is that within-country increases in GDP per capita have positive effects on the income shares accruing to the 1st, 2nd, 3rd, and 4th quintile (low-income and middle-class), but negative effects on the income share accruing to the 5th quintile.

As can be seen from Panel B in Table 1, the LS estimates yield an insignificant relationship between national income and income inequality when controlling for country and year fixed effects. This is also the case in Panel C, where instead of the log of GDP per capita, we include the level of GDP per capita and a squared term to capture the potential U-shaped Kuznets relationship in the regressions. Moreover, the p-value from a test of the hypothesis that the coefficient on the linear and squared GDP per capita term is equal always exceeds 0.1. This suggests that we find no evidence of a Kuznets relationship in the data.

In comparison to the 2SLS estimates, the LS estimates are smaller and statistically insignificant. One reason for the insignificant LS estimates could be measurement error. Classical measurement error attenuates the LS estimates towards zero, but not the IV estimates. Another reason for the smaller least squares estimates could be the reverse causality from inequality to GDP per capita.[7] In addition, other variables which are omitted from equation (1) could lead to inconsistent LS estimates. However, under the assumption that our instruments are exogenous, these omitted variables would not lead to inconsistent 2SLS estimates.

To test for quality of our instrumental variables regressions, we report the first-stage Kleibergen-Paap F-statistic, a measure of the instruments' relevance. This test statistic is well in excess of 10 in all regressions. Thus, we can reject weak instrument bias according to the criterion provided in Staiger and Stock (1997). To examine instrument validity we follow the literature and report the Hansen J test. This is a joint test of the hypothesis that the

[6] Appendix Table 3 shows the first stage effects of OPS and TWWI on countries' real GDP per capita. As expected from previous literature (e.g. Brueckner et al., 2012; Acemoglu et al., 2008) the instruments' first-stage fit is positive and highly significant.

[7] See, for example, Bruckner et al. (2010) who show both empirically and theoretically that greater inequality is associated with a higher return to capital.

instruments are uncorrelated with the second-stage error term. The p-value of the Hansen J test is always in excess of 0.1, suggesting that we cannot reject the hypothesis that the instruments are valid.

With regards to the oil price shock variable, one of the key identifying assumptions in the 2SLS estimation is that countries are price takers in the international oil market. This appears to be a plausible assumption as the majority of countries in our sample only import (export) a small share of world oil imports (see Appendix Table 2 for the list of countries). To further substantiate this point, Table 2 reports 2SLS estimates that exclude both large oil importing and exporting countries (defined by Brueckner et al., 2012, as countries that import or export more than 3 percent of world oil production). The main thrust of our baseline findings continues to hold up.

A specific concern relating to the exclusion restriction is that the oil price instrument may have a direct effect (beyond its effect on national income) on income distribution. This could arise on account of regional, within-country inequalities in the distribution of oil. In order to gauge whether this concern suggests a violation of the exclusion restriction in our baseline regressions, it is useful to recall that the oil price instrument is the interaction between the change in the international oil price and countries' oil net-export GDP shares. In other words, identification is achieved through the differential effect that a change in the international oil price has on countries depending on cross-country differences in oil net-export GDP shares. If these oil net-export GDP shares were systematically correlated with the regional within-country distribution of oil, the exclusion restriction would be violated in our regressions. Unfortunately, cross-country data on the within-country distribution of oil does not exist for a large sample of countries.

We assessed whether countries' oil net-export GDP shares are systematically correlated with cross-country average differences in income inequality. The correlation coefficient between countries' average oil net-export GDP shares and the Gini coefficient is 0.11. A regression of the Gini coefficient on the oil net-export GDP shares yields a t-value of 1.01, implying that statistically we cannot reject the hypothesis of a zero cross-country relationship between oil net-export GDP shares and income inequality. In order to further allay concerns relating to a violation of the exclusion restriction, we also examined the effect of the oil price instrument on measures of countries' income inequality conditional on GDP per capita. The main finding (reported in Table 3) is that the conditional effects of the oil price instrument are insignificant. Hence, there is no evidence the oil price instrument has a direct effect on income inequality beyond its effect on GDP per capita.

As oil revenues could potentially be distributed more equally in more democratic countries, we constructed an interaction term between OPS and the Polity2 score (re-scaled to lie between 0 and 1, with higher values denoting stronger democratic institutions). Appendix Table 4 (Panel A) shows that including this interaction term in the regression does not alter our results. Panel B reports estimates where the interaction term is constructed as the interaction between OPS and an indicator variable that is unity if the original Polity2 score (which ranges between -10 and 10) is strictly positive. As can be seen from the regression estimates, the coefficients on the interaction terms are insignificant. In both instances, GDP per capita continues to have a significant negative effect on inequality.

V. Robustness Checks

A. Alternative Model Specifications

In this sub-section we examine the robustness of our results to alternative model specifications. In particular, we examine robustness to controlling for the lagged dependent variable, leads and lags of national income, measuring income over longer time horizons (10 years, 15 years and 20 years), estimating the model in first differences, examining different time periods, and sensitivity to outliers.

In Table 4 we show that the findings are robust to controlling for the lagged dependent variable. In this dynamic panel estimation, the lagged dependent variable is instrumented with its first lag in order to avoid biases arising from the presence of the country fixed effects. Further, GDP per capita is instrumented with countries' trade-weighted world income and oil price shocks. We continue to find a significant negative effect of GDP per capita on the Gini coefficient and the share of income held by the fifth quintile. The effects of GDP per capita on the first to the fourth income quintiles remain significantly positive. Similar results are obtained if we use the Blundell-Bond system GMM estimator (Appendix Table 5).

We next examine whether there are significant lead or lag effects of income on inequality (Table 5). Panel A shows that the lead effects of income on inequality are insignificant and quantitatively small, while Panel B shows there are no significant lagged effects. The contemporaneous effect of national income on inequality remains significant, and is of a quantitatively similar magnitude to our baseline estimates.

Our main regressions are based on 5-year non-overlapping panels. The estimated coefficient on log GDP per capita, therefore, captures the effect of a change in national income on a country's income distribution over a 5-year horizon. As pointed out by Halter et al., (2013), who focus on the growth effects of inequality, the time span considered could be relevant for the examining relationship between the two. Table 6 reports 2SLS estimates based on GDP per capita data over 10, 15, and 20-year horizons. Our main finding is that GDP per capita is negatively related to the Gini coefficient and the income share of the 5th quintile, but positively related to the income shares of the other quintiles. Quantitatively the estimated effects are somewhat larger (in absolute size) the longer the time horizon over which GDP is measured.

Inequality has risen across many countries over the past two decades, which suggests that the relationship between income growth and inequality could have potentially changed. Table 7, however, documents that there is no evidence of income growth having a substantially smaller effect on inequality in the post-1990 period. Column (1) shows that the coefficient on the interaction term between GDP per capita and an indicator variable for the post-1990 period is positive when the Gini coefficient is the dependent variable. Quantitatively, the estimated coefficient on the interaction term is small and not significantly different from zero. Columns (2)-(6) show that similar results are obtained if we consider the income quintiles. The interaction term is significant and negative for the fourth income quintile, suggesting the increase in the income share held by the fourth quintile was somewhat smaller in the post-1990 period. However, the overall marginal effect for the post-1990 period of an increase in GDP per capita on the income share held by the fourth quintile is still positive and significant at the 5 percent level.

We also re-estimate our baseline equation in first differences (see Appendix Table 6). The first-difference estimation yields similar results as our baseline levels estimation. In particular, there is a significant negative effect of GDP per capita on the Gini coefficient. Moreover, as before, GDP per capita is negatively to the income share of the 5th quintile, but positively related to the income shares of the other quintiles.

We also examined the sensitivity of our baseline estimates to outliers, including large positive and negative within-country changes in inequality and GDP per capita (Appendix Table 7). In Panel A we report two-stage least squares estimates that exclude the top 5th percentile of positive and negative within-country changes in income inequality. In Panel B we report estimates which exclude the top 5th percentile of positive and negative within-country changes in GDP per capita. The main finding is that excluding observations that could be deemed as potential outliers leaves our second-stage estimates largely unchanged, both statistically and quantitatively.

Additional robustness tests not reported here (but available upon request) include examining the consequences of including country-specific linear time trends (in addition to country and year fixed effects), including dummy variables for different income concepts, income sharing units, coverage, equivalence scales, and survey organizations, and assessing whether there is a differential effect of national income on income distribution between oil net-exporting and importing countries. In all instances, the size of the coefficients on log GDP per capita, as well as the basic thrust of our results, remains largely unchanged.

B. Alternative Inequality and Poverty Data

In this subsection we examine the robustness of our results to alternative inequality and poverty data. Columns (1) and (2) in Table 8 report regression estimates using the Solt (2009) dataset that distinguishes net from market (gross) inequality.[8] Column (1) reports estimates for the Gini coefficient after tax and transfers (net Gini); column (2) reports estimates for the Gini coefficient before tax and transfers (gross Gini). We find that in both instances, the estimated effect of income on inequality is negative. Quantitatively, the estimated coefficients are also of similar size, albeit the estimates for gross Gini (before tax

[8]This dataset, based on the WIID, purports to provide better comparability across countries; it does not, however, include breakdowns by income quintiles.

and transfers) are somewhat higher (-14.57), than the estimates obtained using our baseline Gini data (-8.48).

We further examined robustness of our results to inequality data from the World Development Indicators (WDI, 2013)—which yields a total of 226 observations (about one-third less than in our baseline regressions). Column (3) of Table 8 shows that when using the WDI data on the Gini coefficient, there is a significant negative effect of income (the estimated coefficient is -21.07 with a standard error of 12.75). That increases in national income reduce inequality is also supported by the WDI data for income shares (see columns (4)-(8) of Table 8). There is a significant positive effect on the first and second income quintile; the effect on the third and fourth quintiles, while positive, becomes insignificant; the effect on the fifth quintile is negative and insignificant.

Table 9 reports regression estimates of the relationship between GDP per capita and various measures of poverty. In particular, we consider two commonly used measures of poverty: the poverty gap (defined as the mean shortfall from the poverty line, expressed as a percentage of the poverty line), and the poverty headcount ratio (defined as the percentage of the population living on less than $1.25 or $2.00 a day). In columns (1) and (2), the dependent variables are the poverty gap at $1.25 and $2.00, respectively.[9] In columns (3) and (4) the dependent variables are the poverty headcount ratio at $1.25 and $2.00, respectively.[10] The main finding is that increases in GDP per capita have a negative effect on poverty. Quantitatively, the estimates in Panel A of Table 10 suggest that, on average, a one percent increase in GDP per capita is associated with a significant decrease in the $1.25 ($2.00) poverty gap by around 0.04 (0.07) percentage points; the effect on the poverty headcount ratio is 0.10 (0.11) percentage points. In Panel B, we add year fixed effects to the regression model. The consequence of this is that the second-stage coefficients are quantitatively larger (i.e., more negative) than in Panel A, but standard errors increase as well.

VI. The Role of Economic Development

In this section we examine whether the relationship between GDP per capita and income inequality differs depending on a country's stage of economic development and across regions. Columns (1)-(3) of Table 10 show that we cannot reject the hypothesis that the effects of national income on the Gini coefficient are the same between high and low income countries. This can be seen in column (1) from the insignificant coefficient on the interaction between (time-varying) log GDP per capita and countries' average GDP per capita. The interaction terms is also insignificant if we use a binary indicator variable that is unity for low-income countries (defined according to WDI as countries with GNI per capita below US$4,000) or high-income countries (defined according to WDI as countries with GNI per

[9] This measure reflects the depth of poverty as well as its incidence.

[10] Note that data on poverty are much sparser than that for income inequality (the number of observations for the former is about one-third of the latter).

capita above US$12,000) (columns (2) and (3)). Furthermore, we explored interactions with the share of the population that live in rural areas (column (4)) and the share of workers that are employed in the agricultural sector (column (5)). In all instances, the interaction term is insignificant, while the coefficient on GDP per capita remains negative and significant.

Although the sign of the estimated coefficients on the interaction terms indicate that low levels of economic development weaken the inequality reducing effect of income growth, this difference is not significant in statistical terms. In quantitative terms, we note that the estimated interaction effects are also not very large. In column (1) of Table 10 the coefficient of 0.02 on the interaction between log GDP per capita and countries' average GDP per capita (in thousands US$) suggests that taking a country from the 25th percentile of GDP per capita to the 75th percentiles changes the marginal effect of income on the Gini coefficient (which ranges between 0 and 100) from -8.51 (calculated as -8.57+0.02*2.769) to -8.36 (calculated as -8.57+0.02*10.171). Similarly, in column (4) the coefficient of 5.62 on the interaction between log GDP per capita and countries' average share of the population that lives in rural areas suggests that taking a country from the 25th percentile of the share of the population that lives in rural areas to the 75th percentiles changes the marginal effect of income on the Gini coefficient from -10.19 (calculated as -12.03+5.62*0.328) to -8.61 (calculated as -12.03+5.62*0.607).

Only when log GDP per capita is interacted with an indicator variable that is unity if a country's average Gini coefficient is above the sample median (column (6)), do we find evidence of a significant difference in the marginal effect. However, this heterogeneity is not very large quantitatively, suggesting that the inequality reducing effect of income growth is not economically significant for countries with above-median levels of inequality. For instance, the coefficient of 2.08 suggests that in countries with below-median inequality, the marginal effect is -9.76 (standard error 4.17), while in countries with above median Gini coefficients the marginal effect is -11.84 (standard error 4.70). This suggests that for countries with higher inequality (above median Gini), the impact of higher GDP per capita on inequity appears to be slightly larger than for countries with lower inequality (below median Gini), although quantitatively the results are not large.

Table 11 presents estimates from an econometric model that includes, in addition to the log of GDP per capita, interactions with indicator variables for countries in sub-Saharan Africa, Latin America, and Asia. The findings can be summarized as follows. First, the most significant interaction with GDP per capita is for countries in Latin America. For the Gini coefficient (see column (1)), the interaction term is significantly positive. This suggests that the inequality reducing effects of growth in national income are significantly smaller in Latin America. Looking at income quintiles, (columns (2)-(5)), we find that the effects on the lower (upper) quintiles income shares are smaller (larger) in Latin American countries, thus, reconfirming the previous results. A similar finding is obtained for Asian countries, but not countries in sub-Saharan Africa.

Second, even though the inequality reducing effects of growth are significantly smaller in Latin American and Asian countries, they are still significantly different from zero. This can be seen by summing up the coefficients on the log of GDP per capita with the coefficients obtained on the interaction terms. For example, the overall effect for Latin America in the regression where the dependent variable is the Gini coefficient is -15.25 + 3.01 = -12.25. Since the standard error on this sum of coefficients is 7.12, we can reject the hypothesis that the effect of within-country variations in national incomes on the Gini coefficient is equal to zero at the 10 percent significance levels.

VII. Channels

Our results strongly indicate that increased prosperity, on average, leads to lower inequality. What could possibly account for this decline? In this section, we explore several potential channels mediating this relationship. Theory suggests that increased prosperity helps reduce poverty and inequality by increasing access to adequate schooling (e.g., Galor and Zeira, 1993). Consequently, education is the first channel we examine. To this end, we add measures of education attainment to the right-hand side of the second-stage regression. To the extent that human capital accumulation is a factor explaining inequality reduction, this should reduce the statistical significance of instrumented national income, potentially even rendering it insignificant. We exploit two widely used proxies for educational attainment, the average number of years of schooling, and the share of population with secondary schooling.

Panel A of Table 12 shows that, conditional on education, within-country variations in national income have no significant effect on the Gini coefficient. Panel B reports the unconditional effect (i.e. the impact of income on the Gini coefficient without controlling for education). Comparing the estimates in Panels A and B, it can be seen that the conditional effects of income on the Gini coefficient are substantially smaller than the unconditional effects, while the standard errors barely change. For example, when measuring the impact over a 5-year period and controlling for average years of education in the population aged 15 and above (share of the population with secondary education), the estimated conditional coefficient on GDP per capita is -6.32 (-4.75). The unconditional coefficient is -8.48, or about 34 (78) percent larger in absolute value (columns (1) and (5)). When measuring the impact over a 10-year period, and controlling for average years of education in the population aged 15 and above (share of the population with secondary education), the estimated conditional coefficient on GDP per capita is -5.91 (-4.23). The unconditional coefficient is -8.99, about 52 (113) percent larger in absolute value (see columns (2) and (6)). A similar finding emerges when the conditional and unconditional effect is measured over a 15- or 20-year period.

Panel C of Table 12 shows that income has a significant positive effect on education (see Brueckner and Gradstein, 2013, for a more detailed analysis). In columns (1)-(4) the measure of education is Barro and Lee's (2010) average years of education of the population aged 15 and over. In columns (5)-(8) the relevant measure of education is the share of the population with completed secondary school (also from Barro and Lee (2010)). The positive effect obtains when national income is measured over 5-years as well when it is measured over longer periods (e.g. 10 years, 15 years, or 20 years; see columns (2) and (3), (4) and (6), and (7) and (8), respectively). The quantitative interpretation of the estimated coefficients on income in columns (1)-(4) is that a doubling of national income leads to an approximate increase in average years of education of around 2 years. In columns (5)-(8) the estimated coefficients imply that a doubling of national income leads to an approximate increase in the share of population with secondary education by around 20 percentage points.

Table 12 indicates that the education variable is negatively related to inequality. More importantly, instrumented national income, which was shown to be a significant predictor of inequality in the absence of the education variables, now ceases to be significant in most instances. This should be viewed as an indication that one of the channels through which the inequality reduction effect of national prosperity operates is the human capital channel (as proxied by educational attainment).

To address the issue of a potential endogeneity bias, following Barro and Lee (2010), we use the 10-year lag education of parents' education as an instrument for education. Panel A of Table 13 shows the 2SLS estimates where both GDP per capita and average years of education of the population aged 15 and above are instrumented. The instruments are trade-weighted world income, oil price shocks, and the 10-year lag average years of schooling among the population of 40 years and over. The Kleibergen Paap F-statistic of the joint significance of the instruments in the first stage equations is 11.70; hence the instruments are strong according to the tabulations provided in Stock and Yogo (2005).[11]

Panel B of Table 13 shows two-stage least squares estimates where both GDP per capita and the share of the population with secondary education are instrumented. The instruments are trade-weighted world income, oil price shocks, and 10-year lag share with secondary education among the population of 40 years and over. The Kleibergen Paap F-statistic of the joint significance of the instruments in the first stage equations is 10.62; hence the instruments are strong according to the tabulations provided in Stock and Yogo (2005).[12] Overall, the results indicate that education has a significant negative effect on inequality for

[11] 10-year lag average years of schooling among the population of 40 years and over is a significant predictor for average years of schooling among the population of 15 years and over: in the first-stage equation for average years of schooling the coefficient (standard error) on 10-year lag average years of schooling among the population of 40 years and over is 0.77 (0.07). Trade-weighted world income and oil price shocks have a positive effect on log GDP per capita in this 2SLS estimation: in the first-stage equation for log GDP per capita, the coefficient (standard error) on trade-weighted world income is 0.52 (0.09); for the oil price shock it is 2.67 (1.14).

[12] 10-year lag share of secondary education among the population of 40 years and over is a significant predictor for the share of the population with secondary education aged 15 years and over: in the first-stage equation for share of the population with secondary education aged 15 years and over the coefficient (standard error) on 10-year lag share with secondary education among the population of 40 years and over is 0.84 (0.09). Trade-weighted world income and oil price shocks have a positive effect on log GDP per capita in this 2SLS estimation: in the first-stage equation for log GDP per capita the coefficient (standard error) on trade-weighted world income is 0.47 (0.09); for the oil price shock it is 2.59 (1.11).

the majority of inequality measures while the conditional effect of GDP per capita is quantitatively small and insignificant.

In addition to the education channel, we also examined two other potential channels: financial development (proxied by the ratio of private credit to GDP) and government size (measured by the GDP share of government consumption expenditures). Theory does not point to an unambiguous relationship between financial sector development and inequality. Credit constraints, arising from informational asymmetries, transactions and contract enforcement costs, could impede the flow of capital to poor individuals with high-return projects (Galor and Zeira, 1993), thereby reducing the efficiency of capital allocation and intensifying income inequality. This would suggest that financial sector development could serve to reduce poverty and inequality. Other theories, however, posit that since the poor rely more on informal networks for credit, financial development would only benefit the rich and raise inequality (e.g., Bourginon and Verdier, 2000).

As shown in Table 14, we find little evidence that this channel is as important as education in determining how income growth affects inequality. Column (1) of Table 14 shows that the effect of GDP per capita on the Gini coefficient continues to be negative and significant when controlling for financial sector development in the regression. Column (2) shows that, when including in the regression the share of population with secondary school education, the coefficient on GDP per capita becomes quantitatively smaller and statistically insignificant.

Governments can use their power to tax and spend to attenuate inequality and poverty. To examine the role of government spending in mediating the link between income and inequality, we repeat the above exercise for the GDP share of government consumption expenditures.[13] Column (3) of Table 14 shows that the effect of GDP per capita on the Gini coefficient continues to be negative and significant when controlling for the GDP share of government consumption expenditures in the regression. Column (4) shows that, when the share of population with secondary education is included in the regression, the coefficient on GDP per capita becomes quantitatively smaller and statistically insignificant. This, in turn, suggests that education, more so than financial development or government size, is the key channel through which income growth affects inequality.

VIII. CONCLUDING REMARKS

The relationship between national income and its distribution has occupied a central place in the economic development literature. In this paper, we revisit the causal relationship between

[13] It should be noted, however, that the size of the government per se does not fully reflect the redistributive effect of fiscal policy, as governments can use tax as well as expenditure policies to affect income inequality. Further, different categories of revenues and expenditures could have differential redistributive effects (e.g., higher targeted social transfers could be superior in redistribution terms than higher wage bills). See IMF (2014) for details.

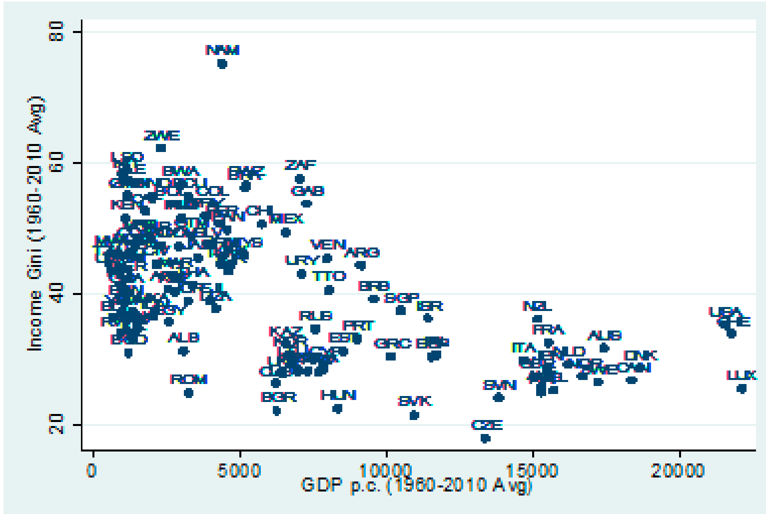
income growth and inequality using plausibly exogenous and persistent sources of variation for national income within countries. In particular, we use two such sources, one based on oil price fluctuations, and the other based on countries' trade-weighted world income. Our results indicate that higher national incomes lead to lower inequality. In particular, our estimations reveal that a one percent increase in GDP per capita, on average, leads to a reduction in the Gini coefficient of over 0.08 percentage points. More specifically, we find that income growth boosts the incomes of the lowest four quintiles at the expense of the top quintile, implying that the poor and the middle class actually benefit from growth.

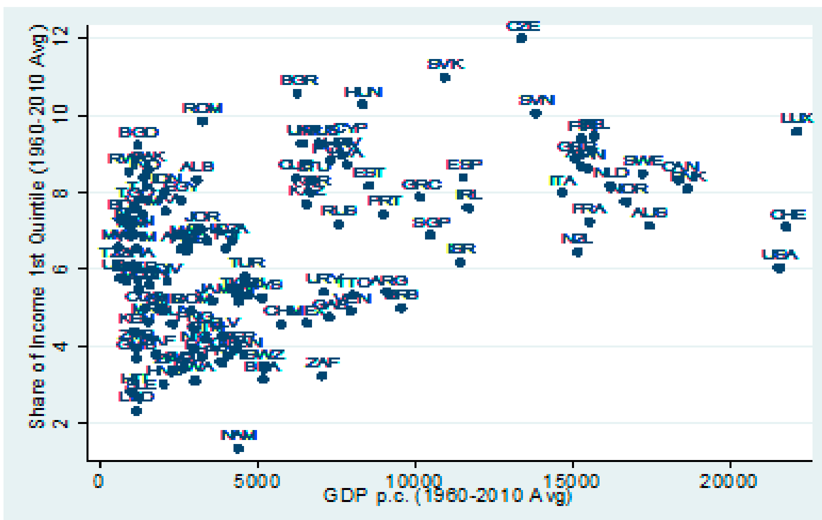
How can we square these results with the observed increase in income (particularly labor and earnings) inequality in many countries in recent decades? A possible interpretation is that the increase in income accruing to the richest quintile that occurred over the past decades is unlikely to be a consequence of a technology neutral increase in GDP per capita. Instead, it could be driven by factors such as skill-biased technological change, which disproportionately benefits higher-skilled workers (OECD, 2012). To the extent that these factors also affect GDP and income inequality beyond their effect on GDP, omitting them from the regressions would lead to biases in simple least square regressions, but not in our instrumented regressions. Importantly, from a policy perspective, our findings suggest that education policies matter. In particular, our findings suggest that in the presence of education proxies, the significance of national income in explaining inequality is substantially reduced.

What do these results imply? Education policies—particularly those that concentrate on equity—may be among the most potent levers countries have to reduce income disparities in the future. These can help improve the income prospects of future generations as educated individuals are better able to cope with technological and environmental changes that directly influence productivity levels. Education policies that help students achieve strong academic outcomes, continue on to higher levels of education, and allow individuals to acquire skills needed to succeed in a globally competitive economy could foster greater intergenerational earnings mobility and reduce income inequality over time. In advanced economies, with an already high share of secondary or tertiary graduates among the working-age population, policies that promote upper secondary or tertiary education would be important. In countries with currently low levels of education attainment, policies that promote equal access to basic education (e.g., cash transfers aimed at encouraging better attendance at primary schools in developing countries, or spending on public capital or education that benefits the poor) could help reduce inequality by facilitating the accumulation of human capital, and making educational opportunities less dependent on socio-economic circumstances.

While the paper has focused on education as a key channel mediating the growth-inequality nexus, future work could adopt a more granular analysis of the role of fiscal policy (e.g., redistributive tax and expenditure policies) in mediating the link between income and inequality. For instance, better access to health services, higher employment, and more efficient safety nets, particularly in developing countries, could also have a bearing on how the inequality reducing effect of income growth materializes. We leave these ideas for future research.

Figure 1. GDP p.c. and Income Inequality
(Cross-Country Scatter Plots, 1960-2010 Average)





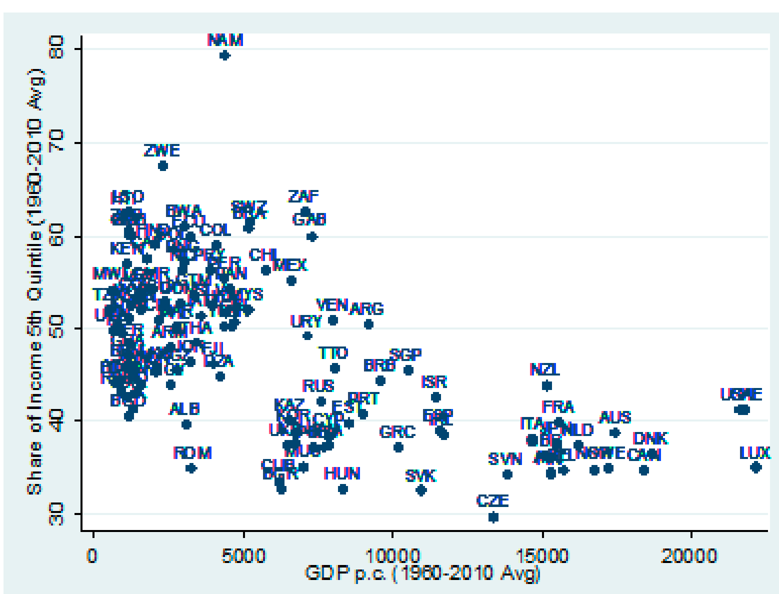


Figure 2. GDP p.c. and Income Inequality
(Cross-Country Scatter Plots, Year 2000)

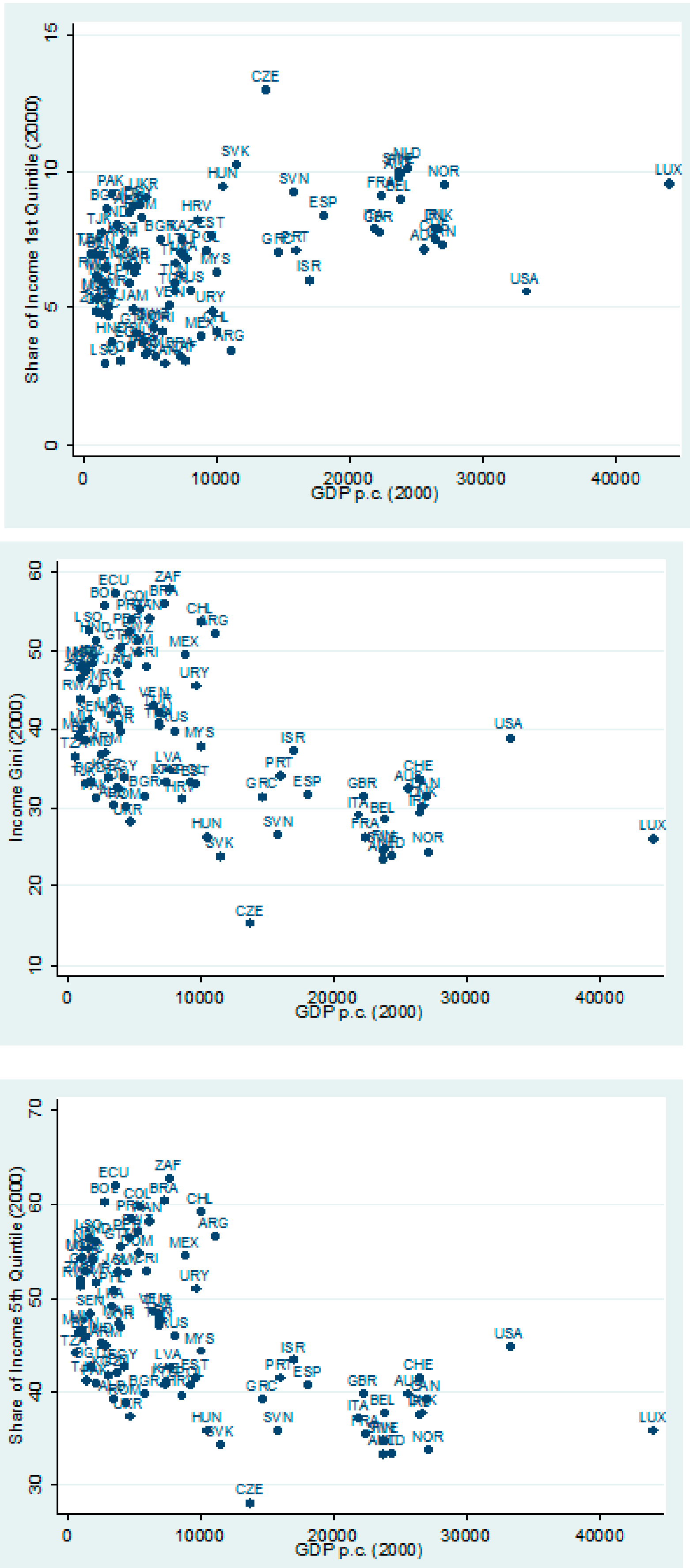


Table 1. Effects of National Income on National Income Inequality
(Baseline)

	Gini	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: 2SLS			
ln(GDP p.c.)	-8.48**	1.43	1.70*	2.01*	2.49***	-7.77**
	(4.09)	(0.94)	(1.06)	(1.09)	(0.89)	(3.52)
Hansen J, p-value	0.47	0.33	0.68	0.62	0.78	0.59
Kleibergen Paap F-Stat	18.52	18.52	18.52	18.52	18.52	18.52
			Panel B: LS			
ln(GDP p.c.)	-2.12	0.54	0.62	0.38	-0.00	-1.52
	(1.58)	(0.35)	(0.44)	(0.50)	(0.46)	(1.44)
R-Squared	0.23	0.10	0.23	0.31	0.04	0.28
			Panel C: LS and Squared GDP p.c. term			
GDP p.c. (in thousands)	-0.120	0.011	0.021	0.037	0.008	-0.081
[A]	(0.249)	(0.069)	(0.073)	(0.068)	(0.067)	(0.211)
GDP p.c. squared (in thousands)	0.000	0.001	0.000	-0.001	-0.001	0.001
[B]	(0.006)	(0.002)	(0.002)	(0.002)	(0.001)	(0.005)
Test [A]=[B], p-value	0.64	0.89	0.78	0.59	0.90	0.70
R-Squared	0.26	0.18	0.22	0.13	0.01	0.20
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	311	311	311	311	311	311
Countries	80	80	80	80	80	80

Note: The method of estimation in Panel A is two-stage least squares; Panels B and C least squares. Huber robust standard errors (shown in parentheses) are clustered at the country level. The instruments in Panel A are trade-weighted world income and oil price shocks. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 2. Effects of National Income on National Income Inequality
(Robustness to Excluding Large Oil Importing and Exporting Countries)

	Gini	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GDP p.c.)	-9.93**	2.10**	2.14**	1.87	2.59**	-8.44**
	(4.00)	(0.84)	(1.06)	(1.16)	(0.97)	(3.60)
Lagged Dependent Var.	0.24***	0.24***	0.22***	0.19**	-0.11	0.19**
	(0.08)	(0.07)	(0.08)	(0.09)	(0.14)	(0.09)
Kleibergen Paap F-Stat	18.45	18.19	18.75	17.60	17.15	18.06
Hansen J, p-value	0.79	0.69	0.89	0.33	0.94	0.67
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	257	257	257	257	257	257
Countries	71	71	71	71	71	71

Note: The method of estimation is two-stage least squares. The excluded countries are Canada, France, Iran, Japan, Norway, USA, United Kingdom, South Korea, and Venezuela. Huber robust standard errors (shown in parentheses) are clustered at the country level. The instruments are trade-weighted world income and oil price shocks. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 3. Effects of National Income on National Income Inequality
(Effects of OPS on Income Inequality beyond GDP)

	Gini	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GDP p.c.)	-9.68**	1.87*	1.97*	2.22*	2.39**	-8.51**
	(4.46)	(0.98)	(1.17)	(1.20)	(1.00)	(3.88)
Oil Price Shock	19.34	-7.08	-2.90	-3.33	1.55	11.90
	(27.02)	(7.28)	(6.99)	(6.72)	(5.65)	(22.23)
Kleibergen Paap F-Stat	32.28	32.28	32.28	32.28	32.28	32.28
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	311	311	311	311	311	311
Countries	80	80	80	80	80	80

Note: The method of estimation is two-stage least squares. Huber robust standard errors (shown in parentheses) are clustered at the country level. The excluded instrument is trade-weighted world income. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 4. Effects of National Income on National Income Inequality
(Controlling for Lagged Inequality)

	Gini	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: 2SLS			
ln(GDP p.c.)	-8.85**	1.54*	1.98**	2.02*	2.53**	-7.92**
	(3.96)	(0.83)	(1.01)	(1.09)	(0.90)	(3.48)
Lagged Dependent Var.	0.23***	0.28***	0.22***	0.16*	-0.08	0.18**
	(0.08)	(0.07)	(0.07)	(0.09)	(0.13)	(0.09)
Hansen J, p-value	0.70	0.38	0.93	0.68	0.93	0.78
Kleibergen Paap F-Stat	19.17	19.35	19.36	18.45	18.40	18.78
			Panel B: LS			
ln(GDP p.c.)	-1.87	0.39	0.56	0.38	-0.04	-1.44
	(1.57)	(0.33)	(0.44)	(0.49)	(0.47)	(1.43)
Lagged Dependent Var.	0.24**	0.30***	0.23***	0.16*	-0.10	0.19**
	(0.09)	(0.07)	(0.08)	(0.10)	(0.12)	(0.09)
R-Squared	0.65	0.60	0.61	0.64	0.11	0.69
			Panel C: LS and Squared GDP p.c. term			
GDP p.c. (in thousands) [A]	-0.071	-0.010	0.010	0.036	0.003	-0.061
	(0.207)	(0.050)	(0.059)	(0.063)	(0.072)	(0.189)
GDP p.c. squared (in thousands) [B]	-0.000	0.001	0.000	-0.001	-0.001	0.001
	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)
Lagged Dependent Var.	0.24**	0.27***	0.23***	0.16*	-0.12	0.19**
	(0.09)	(0.07)	(0.08)	(0.10)	(0.12)	(0.09)
Test [A]=[B], p-value	0.74	0.82	0.87	0.57	0.95	0.75
	0.77	0.70	0.76	0.73	0.24	0.75
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	311	311	311	311	311	311
Countries	80	80	80	80	80	80

Note: The method of estimation in Panel A is two-stage least squares; Panels B and C least squares. Huber robust standard errors (shown in parentheses) are clustered at the country level. The instruments in Panel A are trade-weighted world income and oil price shocks. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 5. Effects of National Income on National Income Inequality
(Lead and Lag Effects)

	Gini	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	Panel A: Current and Future GDP					
ln(GDP p.c.)	-8.05**	1.29	1.73*	1.96*	2.47***	-7.49**
	(4.03)	(0.95)	(1.03)	(1.04)	(0.89)	(3.45)
ln(GDP p.c.), lead	-1.45	0.33	0.12	-0.13	0.86	-1.22
	(3.57)	(0.73)	(0.86)	(1.01)	(1.06)	(3.26)
Kleibergen Paap F-Stat	17.34	17.34	17.34	17.34	17.34	17.34
Hansen J, p-value	0.43	0.28	0.66	0.65	0.97	0.54
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	311	311	311	311	311	311
Countries	80	80	80	80	80	80
	Panel B: Current, Future, and Past GDP					
ln(GDP p.c.)	-7.09*	0.75	1.57	1.95*	2.89**	-7.21**
	(4.25)	(1.04)	(1.09)	(1.12)	(1.25)	(3.26)
ln(GDP p.c.), lead	-0.38	0.32	-0.05	-0.45	0.12	0.05
	(2.74)	(0.67)	(0.70)	(0.72)	(0.81)	(2.38)
ln(GDP p.c.), lag	-0.45	0.59	0.22	-0.19	-1.06	0.50
	(2.33)	(0.57)	(0.59)	(0.61)	(0.69)	(2.02)
Kleibergen Paap F-Stat	23.20	23.20	23.20	23.20	23.20	23.20
Hansen J, p-value	0.35	0.32	0.65	0.47	0.60	0.40
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	311	311	311	311	311	311
Countries	80	80	80	80	80	80

Note: The method of estimation is two-stage least squares. Huber robust standard errors (shown in parentheses) are clustered at the country level. The instruments are trade-weighted world income and oil price shocks. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 6. Effects of National Income on National Income Inequality
(Using GDP over Longer Time Periods)

	Gini	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A: GDP over 10 Years			
ln(GDP p.c., 10 years)	-8.99**	1.69*	1.85*	2.08*	2.34**	-8.00**
	(4.08)	(0.93)	(1.08)	(1.10)	(0.90)	(3.52)
Hansen J, p-value	0.84	0.53	0.99	0.99	0.31	0.97
Kleibergen Paap F-Stat	21.55	21.55	21.55	21.55	21.55	21.55
			Panel B: GDP over 15 Years			
ln(GDP p.c., 15 years)	-10.25**	1.93*	2.15*	2.41**	2.51**	-9.04**
	(4.37)	(1.02)	(1.15)	(1.17)	(0.98)	(3.76)
Hansen J, p-value	0.97	0.65	0.87	0.83	0.19	0.76
Kleibergen Paap F-Stat	21.68	21.68	21.68	21.68	21.68	21.68
			Panel C: GDP over 20 Years			
ln(GDP p.c., 20 years)	-11.63**	2.45*	2.55*	2.54*	2.37*	-9.99**
	(5.53)	(1.30)	(1.48)	(1.47)	(1.26)	(4.75)
Hansen J, p-value	0.95	0.63	0.81	0.77	0.19	0.73
Kleibergen Paap F-Stat	16.23	16.23	16.23	16.23	16.23	16.23
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	311	311	311	311	311	311
Countries	80	80	80	80	80	80

Note: The method of estimation is two-stage least squares. Huber robust standard errors (shown in parentheses) are clustered at the country level. The instruments are trade-weighted world income and oil price shocks. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 7. Effects of National Income on National Income Inequality
(Pre vs. Post-1990 Period)

	Gini	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
	(1)	(2)	(3)	(4)	(5)	(6)
ln(GDP p.c.)	-8.96**	1.54*	2.01**	2.07*	2.63***	-8.07**
	(4.03)	(0.84)	(1.02)	(1.11)	(0.92)	(3.55)
ln(GDP p.c.)*Post 1990 Indicator	0.68	-0.03	-0.15	-0.26	-0.43**	0.81
	(0.97)	(0.13)	(0.16)	(0.18)	(0.21)	(0.62)
Lagged Dependent Var.	0.22***	0.28***	0.21***	0.15*	-0.11	0.17*
	(0.08)	(0.07)	(0.07)	(0.09)	(0.12)	(0.09)
Kleibergen Paap F-Stat	19.10	19.12	19.29	18.61	18.42	18.84
Hansen J, p-value	0.69	0.38	0.93	0.66	0.99	0.76
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	311	311	311	311	311	311
Countries	80	80	80	80	80	80

Note: The method of estimation is two-stage least squares. Huber robust standard errors (shown in parentheses) are clustered at the country level. The instruments are trade-weighted world income and oil price shocks as well as the interaction of these variables with the post-1990 indicator. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 8. Effects of National Income on National Income Inequality
(Alternative Data Sources)

	Solt (2009) Net Gini	Solt (2009) Gross Gini	WDI (2013) Gini	WDI (2013) 1st Quintile	WDI (2013) 2nd Quintile	WDI (2013) 3rd Quintile	WDI (2013) 4th Quintile	WDI (2013) 5th Quintile
	(2)	(3)	(4)	-5	(6)	(7)	(8)	(9)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
ln(GDP p.c.)	-9.20***	-14.57***	-21.07*	4.98**	5.45*	4.53	2.31	-17.29
	(2.30)	(4.32)	(12.75)	(2.48)	(3.05)	(3.22)	(2.90)	(10.94)
Kleibergen Paap F-Stat	17.15	17.15	9.02	9.02	9.02	9.02	9.02	9.02
Hansen J, p-value	0.49	0.43	0.62	0.58	0.51	0.56	0.61	0.67
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	297	297	226	226	226	226	226	226
Countries	76	76	64	64	64	64	64	64

Note: The method of estimation is two-stage least squares. Huber robust standard errors (shown in parentheses) are clustered at the country level. The instruments are trade-weighted world income and oil price shocks.
*Significantly different from zero at the 10 percent significance level,
** 5 percent significance level,
*** 1 percent significance level.

Table 9. Effects of National Income on Poverty

	PovGap $1.25	PovGap $2.00	PovCount $1.25	PovCount $2.00
	(1)	(2)	(3)	(4)
	2SLS	2SLS	2SLS	2SLS
	Panel A: Country Fixed Effects Only			
ln(GDP p.c.)	-3.93**	-6.57***	-9.78**	-11.16***
	(1.80)	(2.43)	(3.90)	(3.34)
Kleibergen Paap F-Stat	6.57	6.57	6.57	6.57
Hansen J, p-value	0.45	0.43	0.55	0.32
Country FE	Yes	Yes	Yes	Yes
Year FE	No	No	No	No
	Panel B: Country and Year Fixed Effects			
ln(GDP p.c.)	-8.96	-15.05	-16.65	-32.61
	(11.24)	(16.06)	(21.69)	(28.12)
Kleibergen Paap F-Stat	4.19	4.19	4.19	4.19
Hansen J, p-value	0.46	0.43	0.59	0.26
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	121	121	121	121
Countries	39	39	39	39

Note: The method of estimation is two-stage least squares. Huber robust standard errors (shown in parentheses) are clustered at the country level. The instruments are trade-weighted world income and oil price shocks and the interaction of these variables with average GDP p.c.. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 10. Effects of National Income on National Income Inequality
(The Role of Economic Development)

	Dependent Variable is Gini Coefficient					
	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
Interaction Term is:	Average GDP p.c.	Low Income Country	High Income Country	Rural Population Share	Agricultural Employment Share	Above Median Inequality
ln(GDP p.c.)	-8.57**	-8.18**	-8.77**	-12.03*	-9.76**	-11.84**
	(4.18)	(4.00)	(3.95)	(6.74)	(4.76)	(4.70)
ln(GDP p.c.)* Interaction Term	0.02	1.03	-1.12	5.62	4.31	2.08**
	(0.08)	(1.01)	(0.86)	(4.47)	(2.94)	(1.02)
Kleibergen Paap F-Stat	18.83	20.57	18.78	12.19	16.81	15.24
Hansen J, p-value	0.48	0.52	0.42	0.38	0.41	0.23
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	311	311	311	311	311	311
Countries	80	80	80	80	80	80

Note: The method of estimation is two-stage least squares. Huber robust standard errors (shown in parentheses) are clustered at the country level. The dependent variable is the Gini income coefficient. The instruments are trade-weighted world income and oil price shocks and the interaction of these variables with the interaction term. The interaction term in column (1) is countries' average GDP per capita; column (2) an indicator variable that is unity if countries' average GDP per capita is below US$4000; column (3) an indicator variable that is unity if countries' average GDP per capita is above US$12000; column (4) countries' beginning of sample share of the population that lives in rural areas; column (5) countries' beginning of sample share of agricultural employment in total employment; column (6) an indicator variable that is unity if countries' average Gini coefficient is above the median. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 11. Effects of National Income on National Income Inequality
(Regional Differences)

	Gini	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
ln(GDP p.c.) [A]	-15.25**	2.82**	3.16**	3.43*	4.31**	-13.71**
	(6.78)	(1.44)	(1.71)	(1.88)	(1.82)	(6.07)
ln(GDP p.c.)* Sub-Saharan Africa [B]	-3.75	0.12	0.81	1.27	1.25	-3.58
	(9.75)	(1.44)	(2.08)	(2.68)	(3.32)	(9.14)
ln(GDP p.c.)* Latin America [C]	3.01**	-1.16***	-0.68**	-0.25	0.37	1.67
	(1.15)	(0.26)	(0.31)	(0.33)	(0.41)	(1.06)
ln(GDP p.c.)* Asia [D]	4.61**	-1.05**	-0.93*	-0.91*	-1.01**	3.85**
	(1.86)	(0.42)	(0.50)	(0.50)	(0.50)	(1.64)
			Implied Effect in Latin America			
[A]+[C]	-10.65**	1.66	2.48	3.18	4.69**	-12.03**
	(5.19)	(1.47)	(1.79)	(2.02)	(1.96)	(6.45)
			Implied Effect in Asia			
[A]+[D]	-12.25*	1.77*	2.23*	2.53*	3.30**	-9.86*
	(7.12)	(1.08)	(1.29)	(1.46)	(1.39)	(4.67)
Kleibergen Paap F-Stat	10.00	10.00	10.00	10.00	10.00	10.00
Hansen J, p-value	0.23	0.11	0.42	0.41	0.80	0.32
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	311	311	311	311	311	311
Countries	80	80	80	80	80	80

Note: The method of estimation is two-stage least squares. Huber robust standard errors (shown in parentheses) are clustered at the country level. The instruments are trade-weighted world income and oil price shocks and the interaction of these variables with indicators that are unity for Sub-Saharan Africa, Latin America, and Asia. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 12. Effects of National Income on National Income Inequality
(Education as a Channel)

	(1) Impact over 5 Years	(2) Impact over 10 Years	(3) Impact over 15 Years	(4) Impact over 20 Years	(5) Impact over 5 Years	(6) Impact over 10 Years	(7) Impact over 15 Years	(8) Impact over 20 Years
	Panel A: The Effect of National Income on Inequality Conditional on Education (Dependent Variable is Gini)							
ln(GDP p.c.)	-6.32	-5.91	-6.91	-8.47	-4.75	-4.23	-4.46	-4.85
	(4.10)	(4.14)	(4.83)	(5.86)	(3.89)	(4.28)	(5.49)	(7.15)
Average Years of Education	-1.17*	-1.56**	-1.26*	-1.60				
	(0.62)	(0.72)	(0.76)	(1.03)				
Share of Population Secondary Education					-0.23***	-0.27***	-0.26***	-0.35***
					(0.07)	(0.08)	(0.09)	(0.14)
Hansen J, p-value	0.53	0.85	0.99	0.97	0.69	0.90	0.92	0.96
Kleibergen Paap F-Stat	19.09	19.91	14.55	11.73	17.57	17.99	13.35	8.21
	Panel B: The Unconditional Effect of National Income on Inequality (Dependent Variable is Gini)							
ln(GDP p.c.)	-8.48**	-8.99**	-10.25**	-11.63**	-8.48**	-8.99**	-10.25**	-11.63**
	(4.09)	(4.08)	(4.37)	(5.53)	(4.09)	(4.08)	(4.37)	(5.53)
Hansen J, p-value	0.47	0.84	0.97	0.95	0.47	0.84	0.97	0.95
Kleibergen Paap F-Stat	18.52	21.55	21.68	16.23	18.52	21.55	21.68	16.23
	Panel C: The Impact of National Income on Education							
	Dependent Variable Average Years of Education				Dependent Variable Share of Population Secondary Education			
ln(GDP p.c.)	1.84***	1.94***	2.10***	1.96***	16.50***	18.20***	20.77***	23.28***
	(0.39)	(0.41)	(0.47)	(0.52)	(4.38)	(4.48)	(4.98)	(6.56)
Hansen J, p-value	0.35	0.77	0.33	0.28	0.13	0.55	0.89	0.84
Kleibergen Paap F-Stat	18.52	21.55	21.68	16.23	18.52	21.55	21.68	16.23
	Controls and Numbers of Observations in Panels A, B, and C							
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	311	311	311	311	311	311	311	311
Countries	80	80	80	80	80	80	80	80

Note: The method of estimation is two-stage least squares. Huber robust standard errors (shown in parentheses) are clustered at the country level. The instruments are trade-weighted world income and oil price shocks and the interaction of these variables with average GDP p.c.. The dependent variable in Panels A and B is the Gini coefficient. In Panel C, columns (1)-(4) the dependent variable is the average years of education of the population 15 and above; in columns (5)-(8) of Panel C the dependent variable is the share of population with secondary education. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 13. Education as a Channel: Instrumenting Both Income and Education

	Gini	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	Panel A: Average Years of Education					
ln(GDP p.c.)	-3.95	0.83	0.54	0.63	1.88**	-3.90
	(4.20)	(0.97)	(1.11)	(1.11)	(0.94)	(3.61)
Average Years of Education	-2.46***	0.33	0.68***	0.75***	0.32	-2.11**
	(0.93)	(0.22)	(0.24)	(0.24)	(0.25)	(0.80)
Kleibergen Paap F-Stat	11.70	11.70	11.70	11.70	11.70	11.70
Hansen J, p-value	0.61	0.37	0.85	0.82	0.68	0.75
	Panel B: Share of Population with Secondary Education					
ln(GDP p.c.)	-3.60	0.07	0.50	1.13	3.05**	-4.90
	(4.11)	(0.97)	(1.07)	(1.15)	(1.23)	(3.67)
Share of Population Secondary Education	-0.29***	0.08***	0.08***	0.05**	-0.03	-0.17**
	(0.09)	(0.03)	(0.02)	(0.02)	(0.04)	(0.08)
Kleibergen Paap F-Stat	10.17	10.17	10.17	10.17	10.17	10.17
Hansen J, p-value	0.78	0.56	0.95	0.87	0.98	0.83
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	311	311	311	311	311	311
Countries	80	80	80	80	80	80

Note: The method of estimation is two-stage least squares. Huber robust standard errors (shown in parentheses) are clustered at the country level. In Panel A the endogenous variables are ln(GDP p.c.) and average years of education; the instruments are trade-weighted world income, oil price shocks, and 10-year lag average years of education among the population of 40 years and over. In Panel B the endogenous variables are ln(GDP p.c.) and share of population with secondary education; the instruments are trade-weighted world income, oil price shocks, and 10-year lag share with completed secondary education among the population of 40 years and over. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Table 14. Financial Development and Government Size as Alternative Channels

Dependent Variable is Gini Coefficient				
	(1)	(2)	(3)	(4)
ln(GDP p.c.)	-11.64***	-6.27	-11.66**	-7.24
	(5.79)	(5.53)	(4.94)	(5.07)
Share of Population Secondary Education		-0.23***		-0.20***
		(0.07)		(0.07)
Domestic Credit/GDP	0.04**	0.02		
	(0.02)	(0.02)		
Government Expenditures/GDP			-0.55*	-0.37
			(0.32)	(0.33)
Hansen J, p-value	0.19	0.48	0.59	0.78
Kleibergen Paap F-Stat	11.44	9.05	13.68	10.55
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	311	311	311	311
Countries	80	80	80	80

Note: The method of estimation is two-stage least squares. Huber robust standard errors (shown in parentheses) are clustered at the country level. The instruments are trade-weighted world income and oil price shocks and the interaction of these variables with average GDP p.c. The dependent variable is the Gini coefficient. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Appendix Table 1. Descriptive Statistics

	Mean	Stdv	Observations
Gini	39.05	10.34	311
1st Quintile	6.50	2.16	311
2nd Quintile	10.84	2.66	311
3rd Quintile	15.13	2.58	311
4th Quintile	21.46	2.21	311
5th Quintile	46.10	8.86	311
ln(GDP p.c.)	8.11	1.29	311

Appendix Table 2. List of Countries

Argentina	Guatemala	Norway
Australia	Guyana	Pakistan
Austria	Honduras	Panama
Bangladesh	Hungary	Paraguay
Barbados	India	Peru
Bolivia	Indonesia	Philippines
Brazil	Iran	Poland
Burundi	Ireland	Portugal
Cameroon	Israel	Rwanda
Canada	Italy	Senegal
Chile	Jamaica	Sierra Leone
Colombia	Japan	South Africa
Costa Rica	Jordan	Spain
Cote d'Ivoire	Kenya	Tanzania
Cuba	Korea, Rep.	Thailand
Denmark	Malawi	Trinidad and Tobago
Dominican Republic	Malaysia	Tunisia
Ecuador	Mali	Turkey
Egypt	Mauritania	USA
El Salvador	Mexico	Uganda
Fiji	Moldova	United Kingdom
Finland	Morocco	Uruguay
France	Mozambique	Venezuela
Gabon	Nepal	Vietnam
Gambia	Netherlands	Zambia
Ghana	Nicaragua	Zimbabwe
Greece	Niger	

Appendix Table 3. First Stage Effects of OPS and TWWI on National Income

	Dependent Variable is ln(GDP p.c.)								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Baseline	Controlling for Lagged Inequality	Controlling for Average Years of Education	Controlling for Share of Population with Secondary Education	Controlling for Average Years of Education and GDP Share of Domestic Credit	Controlling for Share of Population with Secondary Education and GDP Share of Domestic Credit	Controlling for Average Years of Education and GDP Share Government	Controlling for Share of Population with Secondary Education and GDP Share of Government	Excluding Large Oil Importing and Exporting Countries
OPS	2.64**	2.73**	2.67**	2.63**	2.91**	2.89**	2.05*	2.00**	2.78**
	(1.15)	(1.16)	(1.15)	(1.12)	(1.18)	(1.12)	(1.06)	(1.02)	(1.40)
TWWI	0.50***	0.50***	0.51***	0.49***	0.34***	0.28***	0.44***	0.41***	0.50***
	(0.09)	(0.09)	(0.09)	(0.09)	(0.08)	(0.08)	(0.10)	(0.10)	(0.08)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	311	311	311	311	311	311	311	311	257
Countries	80	80	80	80	80	80	80	80	71

Note: The method of estimation is least squares. Standard errors (shown in parentheses) are clustered at the country level. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Appendix Table 4. Controlling for Interaction OPS*Democracy

	Gini	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
			Panel A: Polity2 Score			
ln(GDP p.c.)	-9.18**	1.75*	1.85*	2.09*	2.40**	-8.14**
	(4.38)	(0.96)	(1.14)	(1.19)	(0.98)	(3.82)
OPS*Polity2 Score	0.28	-0.14	-0.13	-0.02	0.04	0.13
	(0.66)	(0.19)	(0.17)	(0.16)	(0.14)	(0.54)
Kleibergen Paap F-Stat	16.49	16.49	16.49	16.49	16.49	16.49
Hansen J, p-value	0.41	0.41	0.46	0.39	0.99	0.45
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	311	311	311	311	311	311
Countries	80	80	80	80	80	80
			Panel B: Democracy Indicator			
ln(GDP p.c.)	-9.73**	1.88*	2.03*	2.27*	2.32**	-8.55**
	(4.41)	(0.98)	(1.17)	(1.18)	(0.99)	(3.84)
OPS*Democracy Indicator	0.19	-0.07	-0.02	-0.03	0.01	0.12
	(0.28)	(0.08)	(0.07)	(0.07)	(0.06)	(0.23)
Kleibergen Paap F-Stat	16.16	16.16	16.16	16.16	16.16	16.16
Hansen J, p-value	0.83	0.93	0.44	0.51	0.50	0.86
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	311	311	311	311	311	311
Countries	80	80	80	80	80	80

-Note: The method of estimation is two-stage least squares. Huber robust standard errors (shown in parentheses) are clustered at the country level. The instruments are trade-weighted world income and oil price shocks. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Appendix Table 5. SYS-GMM Estimation

	Gini	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
	(1)	(2)	(3)	(4)	(5)	(6)
	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM	SYS-GMM
ln(GDP p.c.)	-12.88***	1.38*	1.65**	1.73**	1.69**	-10.83***
	(3.58)	(0.75)	(0.75)	(0.81)	(0.88)	(3.05)
Lagged Dependent Variable	0.13	0.21**	0.16**	0.16**	-0.02	0.10
	(0.09)	(0.09)	(0.08)	(0.07)	(0.06)	(0.08)
AR (1), p-value	0.02	0.01	0.00	0.00	0.07	0.02
AR (2), p-value	0.45	0.36	0.84	0.87	0.54	0.58
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	311	311	311	311	311	311
Countries	80	80	80	80	80	80

Note: The method of estimation in is system-GMM. Standard errors are clustered at the country level. The instruments for log GDP per capita are trade-weighted world income and oil price shocks; the instrument for the lagged dependent variable is its first lag. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Appendix Table 6. First-Difference Specification

	ΔGini	Δ1st Quintile	Δ2nd Quintile	Δ3rd Quintile	Δ4th Quintile	Δ5th Quintile
	(1)	(2)	(3)	(4)	(5)	(6)
Δln(GDP p.c.)	-23.95**	2.91*	6.91**	2.99	7.41**	-20.45**
	(11.50)	(1.60)	(3.17)	(3.82)	(3.77)	(10.68)
Hansen J, p-value	0.96	0.84	0.62	0.54	0.92	0.98
Kleibergen Paap F-Stat	4.47	4.47	4.47	4.47	4.47	4.47
Country FE	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	311	311	311	311	311	311
Countries	80	80	80	80	80	80

Note: The method of estimation is two-stage least squares. Huber robust standard errors (shown in parentheses) are clustered at the country level. The instruments are trade-weighted world income and oil price shocks. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

Appendix Table 7. Excluding Potential Outliers

	Gini	1st Quintile	2nd Quintile	3rd Quintile	4th Quintile	5th Quintile
	(1)	(2)	(3)	(4)	(5)	(6)
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	Panel A: Excluding Large Positive and Negative Within-Country Changes in Inequality					
ln(GDP p.c.)	-8.17**	1.52**	1.86*	1.79	2.53**	-7.18**
	(3.78)	(0.76)	(0.99)	(1.11)	(1.03)	(3.46)
Lagged Dependent Var.	0.43***	0.38***	0.36***	0.32***	-0.09	0.38***
	(0.08)	(0.07)	(0.07)	(0.09)	(0.15)	(0.09)
Hansen J, p-value	0.86	0.39	0.76	0.46	0.60	0.95
Kleibergen Paap F-Stat	16.21	16.37	16.32	15.87	15.70	15.91
	Panel B: Excluding Large Positive and Negative Within-Country Changes in GDP					
ln(GDP p.c.)	-9.10**	1.92**	1.90*	1.99*	2.24**	-7.83**
	(4.36)	(0.93)	(1.15)	(1.16)	(0.97)	(3.78)
Lagged Dependent Var.	0.23***	0.31***	0.22***	0.20**	0.05	0.20**
	(0.09)	(0.07)	(0.08)	(0.10)	(0.11)	(0.09)
Hansen J, p-value	0.67	0.37	0.73	0.93	0.80	0.79
Kleibergen Paap F-Stat	15.26	15.73	15.51	14.63	15.12	14.93
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	295	295	295	295	295	295
Countries	80	80	80	80	80	80

Note: The method of estimation is two-stage least squares. Panel A excludes the top and bottom 5th percentile of within-country changes in the dependent variable; Panel B excludes the top and bottom 5th percentile of within-country changes in the explanatory variable (GDP). Huber robust standard errors (shown in parentheses) are clustered at the country level. The instruments are trade-weighted world income and oil price shocks. *Significantly different from zero at the 10 percent significance level, ** 5 percent significance level, *** 1 percent significance level.

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