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Does wealth inequality matter for growth? The effect of billionaire wealth, income distribution, and poverty☆

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ABSTRACT

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A fundamental question in social sciences relates to the effect of wealth inequality on economic growth. Yet, in tackling the question, researchers have had to use income as a proxy for wealth. We derive a global measure of wealth inequality from Forbes magazine's listing of billionaires and compare its effect on growth to the effects of income inequality and poverty. Our results suggest that wealth inequality has a negative relationship with economic growth, but when we control for the fact that some billionaires acquired wealth through political connections, the relationship between politically connected wealth inequality and economic growth is negative, while politically unconnected wealth inequality, income inequality, and initial poverty have no significant relationship. *Journal of Comparative Economics* **43** (3) (2015) 505–530. Villanova School of Business, Villanova University, Villanova, PA, USA; School of International and Public Affairs, Columbia University, NY, USA and CEPR, IZA, CERGE-EI.

1. Introduction

A central question in the social sciences is whether inequality in control over a society's resources facilitates or hinders economic growth. Although there is a large theoretical and empirical literature on this topic, the question is far from settled.

Three important features of the literature contribute to this lack of consensus. First, although theoretical arguments are usually based on the distribution of wealth, nearly all empirical studies use the distribution of income rather than wealth because data on the distribution of wealth do not exist for a sufficient number of countries. As Aghion et al., (1999, pp. 1617–1618) explain, "… the absence of data on the distribution of wealth for a sufficient number of countries forces researchers to use proxies in empirical studies. The most common approach is to use data on income inequality as a proxy for wealth inequality." Bénabou (1996)

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echoes this point when he notes that the lack of almost any data on the distribution of wealth is a general problem, given that in most theories it is this distribution rather than that of income which is the determinant of outcomes. Finally, while discussing studies that use income inequality, Ravallion (2012, p. 506) emphasizes that "wealth inequality is arguably more relevant though this has been rarely used due to data limitations."[1]

Second, the literature does not adequately account for the sources of inequality. Consider Indonesia and United Kingdom. Although these countries appear similar on measures of income inequality, their respective Gini coefficients being 32.5 and 33.7, they differ markedly on such dimensions as the role that political connections have played in achieving economic success and bringing about their distribution of income and wealth. Yet, virtually all empirical studies ignore this distinction and examine the effects of aggregate measures of inequality on economic growth.[2]

Third, in an important multi-country study, Ravallion (2012) has recently cast serious doubt on inequality as a determinant of growth, suggesting that it is initial poverty rather than income inequality that affects economic growth of countries.

In this paper, we address the shortcomings noted in the first two points above and we provide new evidence on the third point, namely the issue of whether inequality or poverty affects growth. The foremost contribution of our paper is in developing a measure of wealth inequality based on Forbes magazine's annual world-wide listing of billionaires. Second, we introduce two new variables reflecting the extent, if any, to which billionaire wealth has been obtained through political connections (cronyism). We next use annual data for 1987–2007 to construct four five-year panels and test hypotheses regarding the effects on growth of our overall measure of wealth inequality, our measures of politically connected and unconnected wealth inequality, income inequality, and poverty. To the best of our knowledge, ours is the first paper to examine the relationship between wealth inequality and economic growth in a cross-country, panel data setting. It estimates an encompassing model that compares the relationship between economic growth and wealth inequality, income inequality, and poverty.[3] Our econometric analysis, covering the period 1987–2007, is complementary to the larger historical study of Piketty (2014) who constructs data on income and wealth distribution and examines their relationship to economic growth over many decades and even centuries.[4]

We also tackle a methodological criticism of much of the literature in this area, namely that findings may be biased on account of endogeneity of inequality in the growth regressions. We follow one of the leading empirical studies in this area – Forbes (2000) – and estimate a fixed effects model with lagged values of the explanatory variables. In addition, while finding valid instruments for traditional instrumental variable (IV) estimation is very difficult in this setting, we also discuss estimates based on two time-varying IVs for wealth inequality. Finally, we find that our main results pertaining to the relationship between wealth inequality and economic growth hold when we use random effects or system-GMM or difference-GMM methods in estimation.

Our first finding suggests that wealth inequality has a negative, statistically significant relationship with economic growth, while the effect of income inequality is insignificant or only borderline significant, and the effect of poverty is statistically insignificant in nearly all specifications. Hence, using an encompassing model, we show that in the head-on comparison it is wealth inequality, rather than income inequality or poverty that is significantly related to economic growth.

Our second set of results comes from specifications in which we control for the fact that some billionaires acquired wealth through the use of political connections or cronyism, while others obtained it in a relatively standard legal environment. This estimation is based on a categorization of billionaires that is somewhat subjective.[5] We are conservative about classifying someone as being politically connected and are also fully up-front about how we carry out the classification. Using the classification, our results suggest that politically connected wealth inequality and growth are negatively related, while the effects of politically unconnected wealth inequality, income inequality, and initial poverty are statistically insignificant. The second set of results hence suggests that one needs to pay attention to the sources and nature of wealth inequality.

Our third set of results shows that our estimates are robust to a number of alternative specifications and explores the reason why our results with respect to income inequality differ from those of Forbes (2000) and those with respect to poverty from those of Ravallion (2012).

The structure of the paper is as follows. In Section 2, we offer a brief review of the theoretical and empirical literature that examines the impact of inequality and poverty on growth. In Section 3, we present our empirical strategy and describe the data set used. In Section 4, we validate the use of the inequality variables constructed from Forbes magazine's annual listing of billionaires as reasonable measures of wealth inequality and the importance of political connections in a country's socioeconomic system. In Section 5, we present the main results capturing the impact of wealth inequality (and its components),

[1] The only study that directly uses wealth inequality data and looks at the effect of wealth inequality on growth is a paper by Ravallion (1998) who studies the effect of geographic differences in the distribution of wealth on growth in China and finds evidence that high wealth inequality impedes growth.

[2] Easterly (2007) is a notable exception in that he distinguishes between structural and market-based inequality. A fuller discussion of the relationship between his paper and our work is provided in Sections 2 and 4 below. Moreover, as we discuss below, Morck, Stangeland, and Yeung (2000) note that when they divide billionaires into those who were self-made versus those who inherited their wealth, a country's per capita GDP grows faster if its self-made billionaire wealth is larger as a fraction of GDP and slower if inherited billionaire wealth is larger as a fraction of GDP.

[3] As we discuss below, a pioneering study by Alesina and Rodrik (1994) and an important later study by Deininger and Olinto (2000) use land inequality as a proxy for wealth inequality, but this measure is more appropriate for low income agrarian societies than the world as a whole.

[4] Piketty's main point is that historically the rate of return on capital (wealth) exceeds the rate of growth of the economy and that after a hiatus in the second half of the twentieth century it will continue to do so. As a result, the income and wealth of the rich (who live off of return on capital and save-and-invest most of it) will grow faster than the average income from work. This will lead to an increasing inequality in both wealth and income.

[5] This is in the same vein as the Corruption scores of the International Country Risk Guide (ICRG) of the University of Maryland, Transparency International's Corruption Perceptions Index, and Fisman's classification scheme (2001) which are also based on perceptions rather than on objective data.

income inequality, and poverty on growth. We also report a number of robustness checks that show that our findings are robust. Section 6 offers concluding remarks and outlines potential avenues for future work.

2. The literature on the relationship between inequality, poverty, and economic growth

The early view espoused by Kuznets (1955) and Kaldor (1956, 1961) was that economic development affects income distribution, with growth increasing income inequality in the first stages of economic development and reducing it later (the "inverted-U hypothesis"). Kuznets' hypothesis has been extensively tested and generally has been found to lack empirical support (see, e.g., Fields, 2001 for a review).

In the more recent literature on growth and development the causation between inequality and growth runs in the opposite direction.[6] The focus is on the effect of wealth inequality and to a lesser extent income inequality on economic growth, with the theoretical literature yielding two main strands of studies. The first strand suggests various transmission mechanisms through which greater initial inequality fosters economic growth. Prominent among them is a higher savings propensity of the rich (Bourguignon, 1981) and investment indivisibilities (Attanasio and Binelli, 2003). The other strand identifies economic and political channels through which inequality may be harmful for growth. These include redistributive taxation that would be favored by the median voter and which would reduce incentives and hence also growth (Meltzer and Richard, 1981; Alesina and Rodrik, 1994; Barro, 1999), credit constraints generated by low levels of collateral by the poor (Galor and Zeira, 1993), sociopolitical instability stemming from the sense of relative deprivation by the poor (Gupta, 1990), and increased fertility among the poor who cannot afford to provide human capital to their children (De La Croix and Doepke, 2003). The idea common to many of these conceptual frameworks that expect a negative effect of wealth inequality on growth is that extreme wealth concentration distorts economic policies and therefore leads to poor economic performance.

As mentioned earlier, the absence of data on the distribution of wealth for a sufficient number of countries has led empirical researchers to rely on alternatives, typically by using data on income inequality as a proxy for wealth inequality. Two partial exceptions are a pioneering study by Alesina and Rodrik (1994) and an important later study by Deininger and Olinto (2000) that use land holdings as a measure of wealth inequality. However, as Alesina and Rodrik (1994) note, land is only one component of wealth and moreover, land does not exactly fit their model's notion of capital as an accumulating asset. In addition, while inequality in land holding may be appropriate for poor agrarian economies, it is not an adequate proxy for wealth inequality in more developed economies.[7] In addition, our calculations based on the 26 countries for which data exist indicate that there is no correlation between the Gini coefficient for land (sourced from Deininger and Olinto (2000)) and Gini coefficient for wealth, nor do we find a correlation between the 20 countries for which we have data on the Gini coefficient for land and the share of wealth going to the top decile of the population of a country.[8] In contrast, our measure of billionaire wealth normalized by GDP is positively correlated with the Gini coefficient for wealth and the share of wealth going to the top decile.

Interestingly, as Davies et al. (2008) point out, "in all countries which have the requisite data, wealth distribution is more unequal than income." This raises the question as to whether the estimated effect of income inequality on growth truly captures the impact of wealth inequality on growth and it provides one motivation for our study.

The empirical literature dealing with income inequality and economic growth is based on cross-country regressions and, more recently, on panel data analysis. While cross-country regressions examine the long-run relationship and generally find a negative impact of income inequality on growth (see e.g., Alesina and Rodrik, 1994; Persson and Tabellini, 1994; and Perotti, 1996), panel data estimates aim at measuring the short and medium-term relationship and they obtain mixed evidence (see e.g., Forbes, 2000 and Barro, 2000).[9]

A possible reconciliation of the opposing views on whether inequality has a positive or negative impact on growth is made by Easterly (2007, p. 756) who notes:

> One confusion in the theoretical and empirical analysis of inequality is between what we could call structural inequality and market inequality. Structural inequality reflects such historical events as conquest, colonization, slavery, and land distribution by the state or colonial power; it creates an elite by means of these non-market mechanisms. Market forces also lead to inequality, but just because success in free markets is always very uneven across different individuals, cities, regions, firms, and industries. So the recent rise in inequality in China is clearly market-based, while high inequality in Brazil or South Africa is just as clearly structural. Only structural inequality is unambiguously bad for subsequent development in theory; market inequality has ambiguous effects — it could have some of the adverse effects cited in the above models, but eliminating it would obviously have negative incentive effects.

As we discuss later, our first step toward quantifying the importance of political connections goes in the direction of operationalizing Easterly's notion of structural inequality.

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[6] A review of this literature may be found in Aghion, Caroli, and García-Peñalosa (1999), Ehrhart (2009), and Galor (2009).

[7] As a study of income tax returns by Bakija et al. (2012) suggests, professionals account for an overwhelming share of the top 1% of income earners in the U.S.: 31% started or manage nonfinancial businesses, about 16% are doctors, 14% are a part of the financial services industry, 8% are lawyers, 5% are scientists and engineers, and about 2% are a part of the sports, entertainment or media industries. It would be hard to argue that for such individuals, their holdings of land capture, to any reasonable degree, their asset holdings.

[8] Both measures of wealth inequality are sourced from Davies et al. (2008).

[9] Another strand of the literature examines the relationship between growth spells and inequality and finds that high levels of inequality increase the likelihood that a growth spell will end (Berg, 2012 and Ostry, Berg, and Tsangarides, 2014).

Finally, an important motivation for our study comes from Morck, Stangeland, and Yeung (2000) who find that when they divide the world's billionaires into those who were self-made versus those who inherited their wealth, a country's per capita GDP grows faster if its self-made billionaire wealth is larger as a fraction of GDP and slower if inherited billionaire wealth is larger as a fraction of GDP. They argue that the deleterious consequences of having the very wealthy control a very large fraction of a country's assets can lead to entrenchment, bias capital allocation, retard capital market development, obstruct entry by outsider entrepreneurs, and cumulatively retard economic growth. These observations lead Morck, Wolfenzon, and Yeung (2005) to speculate that "inequality involving new money wealth seems different from inequality involving old money wealth." They suggest that "economists need to think less about concentration of wealth per se and more about concentration of wealth in whose hands."

We use this finding as our point of departure in analyzing the relatively unexplored area of the effect of different sources and nature of wealth inequality on growth. In particular, many countries that generated low rates of economic growth were also characterized by a high level of wealth concentration among entrenched elites, frequently politicians and their cronies. The negative correlation between inequality and growth in a cross-section of countries could thus have more to do with the fact that a large share of the national wealth is held by a small number of politically connected families than with higher tax rates or higher expenditure on transfers and subsidies, which are among the channels through which inequality is often believed to affect growth.

The literature on the effect of poverty *vs.* income inequality on economic growth is represented by an important contribution by Ravallion (2012) who uses country-level data based on household surveys to examine the effect of initial poverty and income distribution on subsequent economic growth. His data set covers 90 countries with two surveys at varying points in time, and most of the estimation is hence carried out in a cross-sectional setting. For about two-thirds of the countries, there are three or more surveys and these countries are used for robustness checks, including the GMM estimation and allowing for country fixed effects. Ravallion's (2012) key cross-sectional result, obtained in an OLS model, is that poverty rather than income inequality affects growth and that the effect of poverty on growth is negative. Moreover, he finds that this result holds in the GMM model but vanishes in the specification with country fixed effects.

3. Data and empirical approach

3.1. Construction of data on wealth inequality

The key new source of data that we use is Forbes magazine's annual listing of billionaires. Although Forbes has been publishing a list of the 400 richest Americans since 1982, it was only in 1987 that it expanded its coverage to the richest individuals and families around the world.[10] We use this latter list and assign each billionaire to a country based on the locus of his business activities, which often coincides with his location. We generate three measures of wealth inequality defined for each year as the sum of the wealth of all the billionaires in a given country divided by either the country's GDP or physical capital stock or population.[11] Our first measure parallels that reported by The Economist (Oct. 13, 2012 issue, SS3–SS6) for several countries and in Section 4.1 we show that our three measures are correlated with other measures of wealth inequality.

Because of the nature of construction of our wealth inequality variables, we focus on the effects of concentration of wealth at the top of the wealth distribution pyramid. Our paper hence belongs to the class of studies that examine inequality via the concentration of wealth or income in the top quantiles rather than taking into account the entire distribution (e.g., Davies et al., 2008; Piketty and Saez, 2003; and Wolff, 2006). Focusing on the top of the distribution is useful because over the last several decades concentration of income and wealth at the top has increased (e.g., Piketty and Saez, 2003; Kopczuk and Saez, 2004, and The Economist, 2012). It is also widely believed that this concentration affects economic and social outcomes (e.g., Stiglitz, 2012), and in a number of countries, including the United States and France, government tax policies have been focused on this group. Finally, as Voitchovsky (2012) notes, inequality in different parts of the income distribution has different effects on growth and a single inequality statistic for the entire distribution is insufficient to capture the effects of inequality on growth. Our results may therefore be seen as reflecting the impact of wealth inequality at the very top of the distribution on growth.

The second prong of our analysis focuses on examining the prediction that the effect of wealth inequality on growth depends on whether wealth has been acquired through political connections. We identify the fraction of billionaire wealth that has been generated through the use of political connections by classifying each billionaire into one of two categories: those who benefited from political connections and those who did not. We start by creating a dummy variable called "Political connections" and set it equal to 1 when we conclude through an *extensive* search on Factiva and LexisNexis using news sources from around the world that political connections had a material part to play in the success of the billionaire. We set this variable equal to 0 when we conclude that political connections have not been crucial to the billionaire's rise to riches even though he may have had prior political connections. The criterion we use for classifying billionaires as having benefited from political connections is that our extensive review of evidence indicates that the person would *not* have become a billionaire in the absence of political

[10] The list of countries that appear on the Forbes' billionaire list in each year is provided in the Data Appendix A2.

[11] As billionaire wealth, GDP, and physical capital stock are expressed in nominal terms, the ratio of billionaire wealth to GDP or billionaire wealth to physical capital stock should not exhibit any secular trends because of inflation.

Table 1
Summary statistics for Forbes' billionaire data.

	1987	1992	1996	2002
No. of countries with billionaires	23	31	38	42
Total billionaire wealth (billions $)	$353	$612	$1,152	$1,649
Billionaire wealth, normalized by GDP	3.5%	3.5%	7.6%	5.4%
Billionaire wealth, normalized by physical capital stock	0.69%	0.90%	1.7%	1.2%
Billionaire wealth, normalized by population	0.035%	0.047%	0.11%	0.10%
Politically unconnected billionaire wealth (billions $)	$ 307	$544	$1028	$1581
Politically unconnected billionaire wealth, normalized by GDP	2.7%	2.5%	6.2%	4.9%
Politically unconnected billionaire wealth, normalized by physical capital stock	0.56%	0.71%	1.5%	1.1%
Politically unconnected billionaire wealth, normalized by population	0.032%	0.043%	0.099%	0.098%
Politically connected billionaire wealth (billions $)	$ 46	$ 68	$ 124	$ 69
Politically connected billionaire wealth, normalized by GDP	0.86%	0.95%	1.4%	0.52%
Politically connected billionaire wealth, normalized by physical capital stock	0.13%	0.19%	0.27%	0.082%
Politically connected billionaire wealth, normalized by population	0.0029%	0.0043%	0.0075%	0.0034%

The summary statistics are calculated only for the countries with billionaires when they have data on all the covariates. In the process, we lose between 1 and 4 countries given the lack of data on control variables depending on the year.
The billionaire list for 1996 is used instead of the billionaire list for 1997. Reasons for using the 1996 list instead of the 1997 list are mentioned in the text and details are provided in the Data Appendix A1.

connections that resulted in favoritism and/or explicit government support.[12] Three examples of billionaires who are classified as politically connected are provided in the Data Appendix A3. A full classification of billionaires into the two categories of politically connected and politically unconnected is available from the authors on request.

As our discussion indicates, our measure is conservative in that only individuals who quite clearly benefited from political connections as a means of becoming billionaires are included in the politically connected category. In fact, in classifying billionaires into the two categories, we distinguish between altering the playing field to benefit a particular individual or group of individuals from a generally pro-business regulatory environment. Thus for instance in Hong Kong or Singapore, all businessmen and entrepreneurs benefit from the pro-business administrations.[13] This is different from the case of, say, Indonesia, where during the Suharto regime it really mattered whether one knew Suharto because that could make all the difference between obtaining a potentially lucrative import license or not (Mobarak and Purbasari, 2005). Or consider the case of Russia, which did not have a single billionaire until 1996, when we observe a sudden spurt in their number on account of the large-scale privatization of state assets that took place as part of Boris Yeltsin's re-election as President. In these cases, after the review of news sources from around the world, we conclude that these individuals profited from ties to politicians and would not have been billionaires without their support. Only in such cases do we classify billionaires as politically connected. In our sample, politically connected billionaires account for anywhere between 4% and 13% of total billionaire wealth, depending on the year under consideration.[14,15]

It turns out that countries where entrenched elites control a large fraction of the country's resources are also likely to be countries where a large fraction of billionaires have reached their status through the reliance on such political connections. In Section 4.2, we offer evidence that our measure of politically connected billionaire wealth is a reasonable proxy for the importance of political connections in a country by showing that it is highly correlated with two widely used measures of corruption and an instrument developed in Easterly (2007).

Our panel begins in 1987, the first year in which the Forbes magazine's list of billionaires from around the world was published. Replicating the five-year panel structure in Forbes (2000) implies using lists from years 1987, 1992, 1997, and 2002. We do so, but because Forbes magazine changed its editorial criteria for inclusion in its billionaire list for the period 1997–2000, we substitute billionaire information from 1996 for 1997. Further details regarding the construction of the wealth inequality variable and the robustness of results to using the 1997 list instead of the 1996 list are provided in the Data Appendix A1.

The unit of observation in our sample is a country-(five year) period combination. Summary statistics for the country-period observations with billionaires in the Forbes' data are provided in Table 1.[16]

[12] We classify a billionaire as politically connected if either the person who originated the wealth benefited from political connections or if the person who was growing the wealth benefited from political connections.

[13] In the 2011 Annual Report of Economic Freedom of the World (Gwartney, Hall, and, Lawson, 2011), Hong Kong and Singapore enjoy the highest rating for economic freedom, a distinction they have held in every single year the report was generated since 1990 (82 and 141 pp.).

[14] By this measure, the countries with the highest level of politically connected wealth inequality are Malaysia, Colombia, Indonesia, Thailand, and Mexico.

[15] Overall, while our classification of billionaires into politically connected and politically unconnected may be viewed as being subjective, we note that the two most widely-used measures of corruption (the Corruption scores of the International Country Risk Guide (ICRG) of the University of Maryland and Transparency International's Corruption Perceptions Index) are also based on perceptions rather than on objective data. Perception is also at the heart of the classification scheme employed by Fisman (2001) in that his measure of the importance of political connections to firms in Indonesia is based on "the subjective assessments of a number of top consultants." Finally, we reiterate that our primary finding – the negative relationship between wealth inequality and economic growth – is *independent* of our classification of billionaires into politically connected or unconnected.

[16] We lose 8 of the 134 country-period observations which have billionaires in the estimation because data on schooling is not available for these observations. These correspond to Saudi Arabia (all 4 years: 1987, 1992, 1996, and 2002), Liechtenstein (1996 and 2002), Russia (2002), and United Arab Emirates (2002).

As may be seen from the table, the number of countries on the Forbes' list grows over time. While only 23 countries appear on the first list in 1987, 42 countries appear on the list by 2002. The average level of wealth inequality in these countries, calculated as the sum of all billionaire wealth in the country normalized by GDP, varies between a low of 3.5% in 1987 and 1992 to a high of 7.6% in 1996. A list of countries which appear in the billionaire lists in each year of the sample is provided in Data Appendix A2.

We supplement the sample that corresponds to the data from the Forbes magazine with countries that do not have billionaires but for which data on all other variables are available. We use these countries in our base regressions and assign them a value of zero for billionaire wealth inequality and its components. In our view, assigning a value of zero is reasonable given the comprehensive nature of Forbes magazine's coverage of billionaires. Nevertheless, it seems plausible that imputing a value of zero to the level of wealth inequality in countries which do not have billionaires on the Forbes' lists may introduce a bias in our estimated coefficients and our conclusions could change once we limit ourselves to only those countries which have billionaires at least once. We discuss the concerns regarding sample selection in detail in Section 5.3.1 on p. 18 and describe the various approaches that we adopt to reassure the reader of the robustness of our results.

For income inequality we use data from the second round of the World Income Inequality Database compiled by the UNU-WIDER project on "Global Trends in Inequality and Poverty". This is the most recent data set on income inequality and it provides data on various measures of income inequality for over 150 countries with most observations drawn from the period between 1970 and 2006. We exclude from the data set all observations that do not cover an entire country or an entire population. Within the subset of surveys that meet our criteria, some inequality measures are based on the household, whereas others are based on the individual. Similarly, some inequality measures are based on income, while others are based on expenditure (or consumption). Given that the Gini coefficient is the most commonly available income inequality measure in the Database (and also the one used in the key study by Forbes, 2000), we use it instead of other possible measures.

Finally, for initial poverty we use the headcount index (H_{it}), given by the proportion of the population living in households with consumption per capita (or income when consumption is not available) below the poverty line and sourced from the World Bank's PovcalNet tool (World Bank, Development Research Group, 2013). Following Ravallion (2012), the poverty line is set at $2 per person per day at 2005 PPP, which is the median poverty line among developing countries. For robustness, we also consider a lower line of $1.25 a day which is the expected value of the poverty line in the poorest countries in terms of consumption per person and obtain similar results as those obtained with the $2 per person per day definition.

3.2. *Empirical approach*

The literature on the effects of income inequality and growth has generated concerns that cross-country, cross-sectional regressions lead to omitted variable bias (Forbes, 2000) and that results are not robust (Levine and Renelt, 1992, and Deininger and Squire, 1998). To overcome these concerns, we use panel data to examine the effects on growth of wealth inequality, income inequality, and poverty. We start by using a fixed effects specification that is similar to Forbes (2000), with the difference being that we use wealth distribution, income distribution, and poverty (rather than just income distribution) as our key regressors of interest. As in Forbes (2000), we regress the real GDP growth rate per capita in a five-year period *t* on the values of the explanatory variables at the end of period *t*-1 (i.e., in the year preceding the start of the five-year period *t*). The literature has maintained that in a fixed effects model the values of the lagged variables may be viewed as being predetermined and therefore unlikely to suffer from problems related to reverse causality (endogeneity). Hence, the initial specification we use is:

$$\begin{aligned}\text{Growth}_{i,t} = {} & \beta_0 + \beta_1\text{Wealth inequality}_{i,(t-1)} + \beta_2\text{Income inequality}_{i,(t-1)} + \beta_3\text{Headcount Poverty}_{i,(t-1)} \\ & + \beta_4\text{Income}_{i,(t-1)} + \beta_5\text{Schooling}_{i,(t-1)} + \beta_6\text{PPPI}_{i,(t-1)} + \beta_7\text{Dummy}_{i,(t-1)} + \alpha_i + \eta_t + \nu_{i,t}\end{aligned} \tag{1}$$

where *i* denotes country and *t* annual time period (with $t = 1, 2, \ldots$ T). Growth is measured as the average annual growth rate in real GDP per capita in country *i* in period *t*, while wealth inequality, income inequality, and headcount poverty have been defined above. "Income" is the real GDP per capita. "Schooling" is the average years of secondary schooling in the male and female populations aged 25 and above, and PPPI is the value of the investment deflator, used as a proxy for market distortions. "Dummy" is set to 1 for all country-period observations which have at least one billionaire and 0 for countries which do not. Country fixed effects α_i are incorporated to account for time-invariant country idiosyncratic factors, while period fixed effects η_t control for global shocks in each period that are common across countries. Finally, $\nu_{i,t}$ is the random error term. Throughout the paper, we cluster standard errors at the country level, thus allowing arbitrary country-specific serial correlation (Bertrand et al., 2004).[17]

As mentioned above, the key new explanatory variable, wealth inequality, is constructed as total billionaire wealth normalized by the country's GDP or physical capital stock or population. The choice of these variables for normalizing is based on the fact that data on the total wealth holdings in each country, the preferred denominator, is unavailable. At the same time, it is essential to normalize the raw billionaire wealth holdings by a measure of the size of a given economy since not doing so would lead to artificially inflated values of wealth inequality for countries with a high per capita income and a large population. Thus, absent measures of wealth holdings for each country, we use GDP, physical capital stock, and population as alternatives for normalizing

[17] We also clustered in both the country and time dimensions for our preferred specifications, following Petersen (2009) and Cameron, Gelbach, and Miller (2008, 2011). Using the "ivreg2" command, we found standard errors are generally *smaller* than what we obtain by clustering only at the country level. Given that, to be conservative, we report results clustering on just the cross-sectional (country) dimension. Further details are provided in the Appendix A5.

billionaire wealth.[18] When using a country's physical capital stock, we generate values of the physical stock of a country by the perpetual-inventory method (Nehru and Dhareshwar, 1993) and re-define wealth inequality as the ratio of the sum of billionaire wealth for a given country in a given year to the total estimated physical stock of capital in that country in that year.[19] As we show later, using GDP, physical capital stock, and population for normalizing billionaire wealth yield mostly similar results.

Since not all countries included in the estimation have billionaires in any given year, we control for this feature by introducing a dummy variable that takes the value of 1 if a country had billionaires in a given year and 0 if it did not. Incorporating this dummy variable into the regression allows country-period observations without billionaires to have different fixed effects than countries with billionaires in any given period. Furthermore, including countries without billionaires allows us to estimate more precisely the effects of the other variables on economic growth.

As mentioned earlier, we develop a proxy variable for the importance of political connections based on a classification of whether political connections had a material role in the success of a given billionaire. We then add up the total wealth of all such politically connected billionaires, normalize the sum by the country's GDP or physical capital stock or population, and call the resulting variable "Politically connected wealth inequality." For the billionaires that did not materially benefit from political connections we add up their total wealth, normalize the sum by the country's GDP or physical capital stock or population and label the variable "Politically unconnected wealth inequality." Thus:

$$\begin{aligned}\text{Billionaire wealth/GDP} &= \text{Politically unconnected billionaire wealth/GDP}\\ &\quad + \text{Politically connected billionaire wealth/GDP}\end{aligned} \tag{2a}$$

Equivalently,

$$\text{Wealth Inequality} = \text{Politically unconnected wealth inequality} + \text{Politically connected wealth inequality} \tag{2b}$$

and analogously for normalization by physical capital stock and population.

The other variables used in specification (1) are relatively standard in the inequality-growth literature. The dependent variable, growth rate in real GDP per capita, is calculated as the average annual compounded growth rate over a five-year period of Gross Domestic Product per capita in constant prices and expressed in national currency (IMF, 2009).[20] Initial income at the start of each period is measured by the log of real GDP per capita in International dollars in 2000 Constant Prices from the Penn World Tables v6.2 (Heston et al., 2006). Schooling is measured as the average years of secondary schooling in the male and female population aged 25 and above (Barro and Lee, 2001). Because data on schooling are unavailable for years 1987, 1992, 1997, and 2002, data from 1985, 1990, 1995, and 2000 are used instead. Finally, PPPI, the Price Level of Investment is calculated by dividing the purchasing power parity (PPP) for investment goods by the US dollar exchange rate. It is used commonly as a proxy for market distortion that affects the cost of investment, such as tariffs, government regulations, corruption, and the cost of foreign exchange. This variable is common in growth regressions and it is also drawn from the Penn World Tables.[21] In addition, we include as key explanatory variables, income inequality and headcount poverty, defined above. Summary statistics for the dependent variable and the explanatory variables for the sample included in the estimation sample are presented in Table 2.

Overall, three considerations have affected our choice of regressors in the basic specification: (i) comparability with the existing literature, (ii) need for parsimony, and (iii) possible endogeneity of some control variables that are typically used in standard growth equations, such as government expenditure and proxies for political and institutional instability (Perotti, 1996; Forbes, 2000).

4. The validity of billionaire wealth as a measure of inequality

In Section 3.1 we have described the nature of our measures of wealth inequality and provided justification for focusing on the top of the wealth distribution pyramid. In this section we provide additional information about the validity of our measures.[22]

4.1. Wealth inequality

To assess further whether normalized billionaire wealth is a useful proxy for wealth inequality, we compare our measure with data on wealth inequality reported by Davies et al. (2008). These authors provide *cross-sectional* data on the share of wealth that is held by the top decile of the population (and the Gini coefficient of wealth) for a set of 20 (26) countries, respectively, of which 18 (22) have billionaires in at least one of the four years of our sample (1987, 1992, 1996, and 2002). Comparisons of our billionaire wealth measure normalized by GDP with the closest-year values of the Davies et al. (2008) measures are reported in Table 3.

[18] Morck, Stangeland, and Yeung (2000) also use a similar measure in their paper and mention the lack of wealth-based Gini coefficients as an obstacle to estimating the effect of inequality in wealth distribution on economic growth.

[19] We use the Stata module, Stockcapit (Amadou, 2011) for this exercise.

[20] Sourced from: http://www.imf.org/external/pubs/ft/weo/2009/01/weodata/index.aspx.

[21] Initial income and PPPI are obtained from the Penn World Tables (http://pwt.econ.upenn.edu/php_site/pwt62/pwt62_form.php). PPPI is frequently used in the macroeconomic and international literature and measures how the cost of investment varies between each country and the United States.

[22] In this section, in the interest of brevity, we only include results when billionaire wealth is normalized by GDP. Results when billionaire wealth is normalized by physical capital stock or population are similar and are available on request. In addition, we note that billionaire wealth, normalized by GDP and billionaire wealth, normalized by physical capital stock are correlated with a correlation coefficient of 0.9552 ($p < 0.001$) and billionaire wealth, normalized by GDP and billionaire wealth, normalized by population are correlated with a correlation coefficient of 0.8085 ($p < 0.001$).

Table 2
Descriptive Statistics for dependent variable and all control variables.

Panel A: Summary statistics

	Definition	Source	Period/ year	Mean	Std. dev.	Minimum	Maximum
Growth rate	Growth in real GDP per capita	IMF World Economic Outlook Database	1988–1992	1.6%	3.9%	−7.4%	9.2%
			1993–1997	1.7%	3.8%	−11.4%	10.3%
			1998–2002	1.2%	2.2%	−3.4%	7.4%
			2003–2007	3.8%	1.7%	0.5%	10.4%
Income	Ln of real GDP per capita in 2000 constant prices (In international dollar per person)	Penn World Tables v6.2	1987	8.09	0.71	6.58	9.23
			1992	7.98	0.81	6.60	9.19
			1997	8.14	0.79	6.67	9.31
			2002	8.24	0.76	6.79	9.44
Female schooling	Average years of secondary schooling in the female population aged 25 and above	Barro & Lee (2001)	1985	0.67	0.45	0.05	1.60
			1990	0.82	0.61	0.05	2.20
			1995	1.00	0.68	0.06	2.49
			2000	1.13	0.67	0.08	2.61
Male schooling	Average years of secondary schooling in the male population aged 25 and above	Barro & Lee (2001)	1985	1.05	0.47	0.30	1.96
			1990	1.16	0.61	0.13	2.37
			1995	1.27	0.70	0.17	3.12
			2000	1.38	0.69	0.16	3.10
PPPI	Price level of investment, measured as the PPP of investment/ exchange rate relative to the US	Penn World Tables v6.2	1987	69.8	62.9	24.9	367.6
			1992	74.6	46.5	31.7	325.0
			1997	68.7	21.8	22.4	111.4
			2002	62.1	25.8	27.0	138.6
Wealth inequality	Billionaire wealth, divided by GDP	Forbes' listings & own estimates	1987	0.2%	0.6%	0.0%	2.3%
			1992	0.7%	1.5%	0.0%	7.2%
			1996	2.6%	6.2%	0.0%	28.2%
			2002	1.2%	2.6%	0.0%	10.1%
Politically unconnected wealth inequality	Politically unconnected billionaire wealth, divided by GDP	Forbes' listings & own estimates	1987	0.0%	0.2%	0.0%	1.1%
			1992	0.3%	0.9%	0.0%	4.7%
			1996	1.8%	4.3%	0.0%	25.6%
			2002	0.9%	2.0%	0.0%	10.1%
Politically connected wealth inequality	Politically connected billionaire wealth, divided by GDP	Forbes' listings & own estimates	1987	0.2%	0.5%	0.0%	2.3%
			1992	0.4%	1.0%	0.0%	4.3%
			1996	0.9%	3.0%	0.0%	18.5%
			2002	0.3%	1.3%	0.0%	8.0%
Income inequality	Gini coefficient of any quality level and with either person or household as the unit of analysis	UNU-WIDER World Income Inequality Database	1987	45.5	10.4	22.7	62.0
			1992	48.7	9.3	29.4	69.5
			1997	50.9	8.2	29.5	71.0
			2002	50.6	8.0	26.7	66.6
Headcount poverty	Percentage of the population in households with consumption per capita below $2/ day	World Bank PovcalNet tool	1987	47.0	31.9	0.1	96.5
			1992	48.5	31.8	0.2	95.2
			1997	43.2	30.5	0.5	92.4
			2002	39.1	27.2	0.2	90.7

Panel B: Pairwise Pearson correlations of variables

		1	2	3	4	5	6	7	8	9	10
1	Growth rate	1									
2	Income	0.16	1								
3	Female Schooling	0.17	**0.70**	1							
4	Male Schooling	**0.26**	**0.57**	**0.83**	1						
5	PPPI	−0.19	−0.13	−0.16	**−0.23**	1					
6	Billionaire wealth inequality	−0.03	**0.29**	**0.36**	**0.33**	−0.11	1				
7	Politically unconnected wealth inequality	−0.04	**0.24**	**0.32**	**0.25**	−0.09	**0.89**	1			
8	Politically connected wealth inequality	−0.01	**0.24**	**0.28**	**0.32**	−0.11	**0.76**	**0.39**	1		
9	Income inequality	**−0.22**	−0.14	−0.01	**−0.28**	**0.24**	0.03	0.07	−0.03	1	
10	Headcount poverty	−0.03	**−0.84**	**−0.68**	**−0.54**	0.02	−0.19	−0.17	−0.15	0.07	1

This table presents summary statistics and Pearson correlation coefficients between the regression variables. Panel A includes the mean, standard deviation, minimum, and maximum. Panel B reports the Pearson correlation coefficients with boldface indicating statistical significance at the 1% level. Growth Rate is the annual rate of growth in real GDP per capita, averaged over a five-year period; Income is the log of Real GDP per capita in 2000 constant prices (in international dollar per person); Female Schooling is the average years of secondary schooling in the female population aged 25 and above; Male Schooling is the average years of secondary schooling in the male population aged 25 and above; PPPI is price level of investment, measured as the PPP of investment/exchange rate relative to the USA; Wealth Inequality is Billionaire wealth, divided by GDP; Politically Unconnected Wealth Inequality is Politically unconnected billionaire wealth, divided by GDP; and Politically Connected Wealth Inequality is Politically connected billionaire wealth, divided by GDP. Income Inequality is the Gini coefficient of any quality level and with either person or household as the unit of analysis. Headcount Poverty is the percentage of the population in households with consumption per capita below $2/day.

Table 3
Wealth distribution data from the Davies et al. (2008) data set & Forbes' list of billionaires.

Panel A: Data on wealth share held by the top decile and billionaire wealth/GDP

Country	Percent of wealth held by the top decile	Year that the wealth statistics pertains to	Closest year(s) in the billionaire list	Billionaire wealth/ GDP in that year(s) (%)
Australia	45	2002	2002	1.36
Canada	53	1999	1996 & 2002	4.38
China	41.4	2002	2002	0.07
Denmark	76.4	1996	1996	2.60
France	61.0	1994	1992	1.27
Germany	44.4	1998	1996	5.37
India	52.9	2002–2003	2002	2.55
Indonesia	65.4	1997	1996	11.88
Ireland	42.3	1987	2002	1.06
Italy	48.5	2000	2002	3.16
Japan	39.3	1999	1996 & 2002	1.73
Norway	50.5	2000	2002	0.67
Republic of Korea	43.1	1988	1987	2.05
Spain	41.9	2002	2002	2.45
Sweden	58.6	2002	2002	15.96
Switzerland	71.3	1997	1996	11.93
United Kingdom	56.0	2000	2002	2.01
United States	69.8	2001	2002	8.28

Panel B: Data on Gini coefficient of wealth and billionaire wealth/GDP

Country	Measure of Gini coefficient in 2000	Billionaire wealth/GDP in 2002 (%)
Argentina	0.74	1.02
Australia	0.622	1.36
Brazil	0.784	2.93
Canada	0.688	6.18
China	0.55	0.07
France	0.73	4.54
Germany	0.667	10.46
India	0.669	2.55
Indonesia	0.764	0.92
Italy	0.609	3.16
Japan	0.547	1.51
Mexico	0.749	4.50
Netherlands	0.65	2.23
Republic of Korea	0.579	0.76
Russia	0.699	4.29
Spain	0.57	2.45
Switzerland	0.803	15.63
Taiwan	0.655	4.74
Thailand	0.71	1.81
Turkey	0.718	6.20
United Kingdom	0.697	2.01
United States	0.801	8.28

Data on share of wealth held by the top decile are available for Finland and New Zealand in the UNU–WIDER data set (Table 1, p. 4) but they do not have billionaires in any of the four years of our sample, 1987, 1992, 1996, and 2002 and hence are not included in Panel A of Table 3. Data on Gini coefficient for wealth are available for Bangladesh, Nigeria, Pakistan, and Vietnam in the UNU–WIDER data set (Table 3, pp. 9–10) but they do not have billionaires in any of the four years of our sample, and hence are not included in Panel B of Table 3.

The raw correlation coefficient and Spearman rank correlation coefficient for the share of wealth going to the top decile and the measure of wealth inequality that we construct (Panel A) for a sample of 18 countries are 0.54 (p-value $= 0.0199$) and 0.58 (p-value $= 0.0122$), respectively.[23] Examining the cross-country correlation between the Gini coefficients of wealth available for 22 countries for the year 2000 from the Davies et al. (2008) data set and the measure of wealth inequality for 2002 constructed in this paper (Panel B) shows a positive and statistically significant correlation of 0.50 at the 2% level ($p = 0.0188$). These positive correlations suggest that our measure of wealth inequality is reasonable.

Our data also reflect the general pattern of increasing inequality around the world that has been noted, among others, by Smeeding (2005), Brandolini and Smeeding (2009), Galbraith (2009), The Economist (2012), Piketty and Zucman (2014), and

[23] This analysis includes Denmark's reported share of wealth going to the top decile of 76.4. The Danish figure is "probably unreliable given the large negative asset holdings reported for half the Danish population" (Davies et al., 2008). Excluding Denmark, the raw correlation coefficient rises to 0.69 (p-value $= 0.0023$) and the Spearman rank correlation coefficient rises to 0.60 (p-value $= 0.0116$).

Saez and Zucman (2014). For example, we find that in 8 of the 22 countries that have billionaires in each of the four years of our sample, wealth inequality, as measured by us, increases monotonically over time. This increase in inequality comes from the combined effect of an increase in the number of billionaires for each country, and a general trend of increasing average billionaire wealth for each country.

In addition, if we compare the level of inequality in 1987, the starting period of our sample, with that in 2002, the last year of our sample, we find that wealth inequality increased in 17 of the 23 countries during this period and declined in only 6 of them. To arrive at a similar measure for the global economy, we look at the same set of countries that have billionaires and limit ourselves to those for which data are available on all the control variables. We add up the total billionaire wealth of all these countries and normalize that by the sum of their GDPs to arrive at a measure of global wealth inequality. Such a measure of global wealth inequality more than doubles for the entire world during this period, starting from a relatively low value of 2.3% in 1987 and culminating in a value of 5.2% in 2002. This rise can be decomposed into a rise in the number of billionaires (or billionaire families) on the list from 167 in 1987 to 495 in 2002, and a rise in the average wealth per billionaire from $2.16 billion in 1987 to $3.46 billion in 2002. Based on these pieces of evidence, we feel that billionaire wealth, normalized by country GDP, physical capital or population, can serve as a reasonable proxy of wealth inequality for a country – measured as concentration of wealth at the top of the distribution.

4.2. Validity of politically connected wealth inequality

To assess whether politically connected billionaire wealth is a reasonable proxy for the importance of political connections and cronyism in a country, we examine the extent to which this measure accords with other proxies such as the extent of corruption in a society. One source of data on corruption is the aforementioned ICRG. Data on corruption in government are available on an annual basis for 100–140 countries (depending on the year) from 1984 to 2009.[24] It thus overlaps with the four years in our sample. We examine the relationship between politically connected wealth inequality and the ICRG Corruption score for all countries that have billionaires using specification (3a) for each individual year and using (3b) when pooling data across all years:

$$\text{Politically connected wealth inequality}_i = \gamma_0 + \gamma_1 * \text{ICRG Corruption Score}_i + \nu_i \tag{3a}$$

$$\text{Politically connected wealth inequality}_{i,t} = \delta_0 + \delta_1 * \text{ICRG Corruption Score}_{i,t} + \eta_t + \nu_{i,t} \tag{3b}$$

where ν_i and $\nu_{i,t}$ are the random error terms in (3a) and (3b), respectively, and η_t in (3b) represent a set of period dummies. Results from estimating specification (3a) are reported in columns (1) to (4) of Panel A in Table 4. Results from estimating (3b) using a pooled OLS approach and a random effects specification are presented, respectively, in columns (5) and (6) of Panel A. The same exercise is repeated in panels B and C, using politically unconnected wealth inequality in Panel B and wealth inequality in Panel C.

The coefficient in the first row of Panel A of Table 4 suggests that our measure of politically connected wealth inequality and the ICRG index of corruption are strongly and positively correlated with each other. Countries that are more corrupt are countries that have a higher fraction of society's resources controlled by politically connected billionaires. In contrast, politically unconnected billionaire wealth normalized by GDP (Panel B) and billionaire wealth normalized by GDP (Panel C) are not significantly correlated with the ICRG Corruption scores. If anything, the negative and statistically significant coefficients in columns (1) and (5) of Panel B of the table suggest that countries that are less corrupt are countries where a higher fraction of society's resources is controlled by billionaires who did not benefit materially from political connections.

We also note that for the five countries with the highest level of politically connected wealth inequality (Malaysia, Colombia, Indonesia, Thailand, and Mexico), the median ranking on the Transparency International's Corruption Perceptions Index[25] was 32 (out of 41 countries) in 1995 and 94 (out of 174 countries) in 2012. In contrast, for the six countries that had billionaires in every year of the sample and yet had no politically connected billionaires in any year (Hong Kong, Netherlands, Singapore, Sweden, Switzerland, and United Kingdom), the median ranking on the Corruption Perceptions Index was 9 (out of 41 countries) in 1995 and 8 (out of 174 countries) in 2012.[26] This also suggests the reasonableness of our classification scheme for billionaires as politically connected and politically unconnected.

Finally, in addition to the regressions presented in Table 4, we have also calculated simple univariate correlations between an IV developed in Easterly (2007) and our measure of political connectedness. Easterly's instrument builds on a body of work by Engerman and Sokoloff (Engerman and Sokoloff, 1997 and Sokoloff and Engerman, 2000) (henceforth ES). ES suggest that factor

[24] Lower scores indicate "high government officials are likely to demand special payments" and that "illegal payments are generally expected throughout lower levels of government" in the form of "bribes connected with import and export licenses, exchange controls, tax assessment, police protection, or loans." The measure ranges in value from 0 to 6, with higher values indicating less corruption. In order to have a higher score correspond to a higher rather than lower level of corruption and also have it range from 0 to 1, we rescale the measure accordingly.

[25] A higher rank on the Corruption Perceptions Index indicates that a country is perceived as being more corrupt by experts knowledgeable about the country. In the most recent 2012 rankings by Transparency International, Denmark, Finland, and New Zealand shared the 1st spot and were viewed as the least corrupt countries in the world, whereas Afghanistan, North Korea, and Somalia shared the 174th spot and were perceived as the most corrupt countries in the world.

[26] Full details are provided in Data Appendix A4.

Table 4
Relationship between billionaire wealth and its components, normalized by GDP and ICRG Corruption Scores.

Year(s) included	(1) 1987	(2) 1992	(3) 1996	(4) 2002	(5) All	(6) All
Panel A: Dependent variable: Politically connected billionaire wealth, normalized by GDP						
ICRG corruption score	0.0364**	0.0426***	0.0410***	0.0226**	0.0347***	0.0231***
	(0.0159)	(0.0136)	(0.0148)	(0.00837)	(0.00645)	(0.00784)
Constant	−0.000419	−0.00155	0.00164	−0.00461*	0.0000741	0.00438
	(0.00170)	(0.00199)	(0.00538)	(0.00272)	(0.00380)	(0.00370)
R2	0.17	0.28	0.060	0.11	0.12	0.047
F	5.212	9.786	7.665	7.309	7.972	
Panel B: Dependent variable: Politically unconnected billionaire wealth, normalized by GDP						
ICRG corruption score	−0.0413**	−0.0228	−0.000	−0.0638	−0.0342*	−0.0322
	(0.0158)	(0.0241)	(0.0544)	(0.0449)	(0.0200)	(0.0202)
Constant	0.0397***	0.0330***	0.0624**	0.0825***	0.0377***	0.0313***
	(0.0104)	(0.0112)	(0.0252)	(0.0262)	(0.00961)	(0.00835)
R2	0.093	0.017	0.000	0.050	0.078	0.23
F	6.791	0.891	0.000	2.019	2.825	
Panel C: Dependent variable: Billionaire wealth, normalized by GDP						
ICRG corruption score	−0.00487	0.0198	0.0409	−0.0411	0.000435	−0.0106
	(0.0208)	(0.0290)	(0.0574)	(0.0455)	(0.0214)	(0.0219)
Constant	0.0393***	0.0315***	0.0640**	0.0779***	0.0378***	0.0368***
	(0.0103)	(0.0112)	(0.0254)	(0.0261)	(0.0101)	(0.00929)
R2	0.0012	0.013	0.0090	0.020	0.066	0.20
F	0.0547	0.466	0.508	0.817	2.288	
Econometric technique	OLS	OLS	OLS	OLS	Pooled OLS	RE
Number of observations	22	31	37	41	131	131

ICRG Corruption score has been rescaled such that higher values indicate more (rather than less) corruption and so that the index ranges from 0 to 1.
Period fixed effects are introduced but not reported in columns (5) and (6).
Random Effects specification has been used in column (6) in preference to Fixed Effects specification based on the results of a Hausman test.
Robust standard errors in parentheses; standard errors are clustered by country in columns (5) and (6).
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

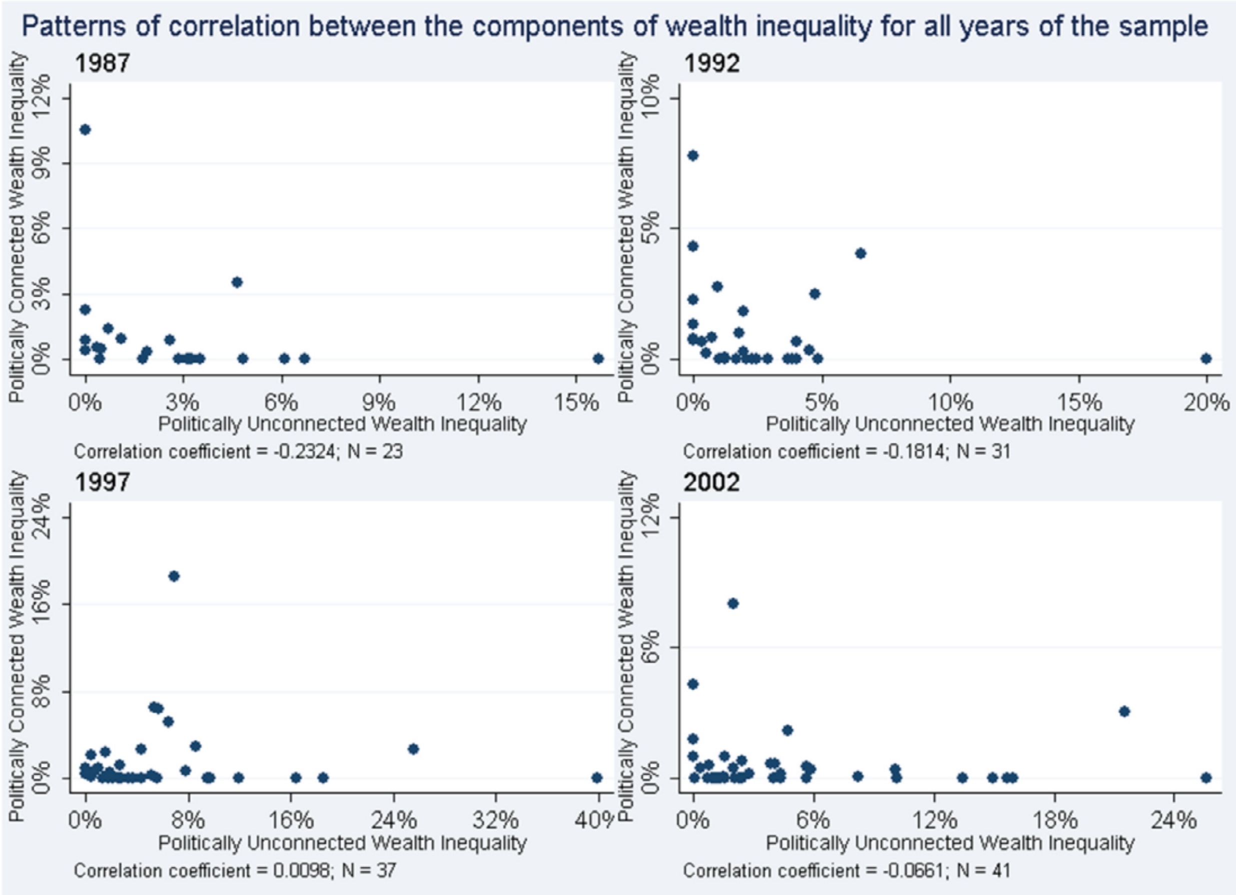
endowments are a central determinant of inequality, which Easterly (2007, p. 756) refers to as structural inequality and contends that:

> …structural inequality in turn is a determinant of bad institutions, low human capital investment, and underdevelopment. ES argues that the land endowments of Latin America lent themselves to commodities featuring economies of scale and the use of slave labor (sugar cane is their premier example) and thus were historically associated with high inequality. In contrast, the endowments of North America lent themselves to commodities grown on family farms and thus promoted the growth of a large middle class. The ES work suggests a natural instrument for inequality: the exogenous suitability of land for wheat versus sugarcane. This instrument is particularly attractive because it picks out the variation due to structural inequality rather than that due to market inequality.

Although it may appear that the suitability of land for wheat versus sugar is simply proxying for whether the country is in the tropics, Easterly provides evidence that there is considerable variation in this variable in both tropical and non-tropical areas. Furthermore, he finds that the differential explanatory power of this IV in the first stage regression survives intact when tropics is independently controlled for.

We examine the correlation between wealth inequality and its two components (politically unconnected and politically connected wealth inequality) and the IV used in Easterly (2007) – the exogenous suitability of land for wheat versus sugar (LWHEATSUGAR).[27] The value of the IV does not vary for a given country over time, and this relationship therefore can only be examined in models without country-specific fixed effects. We hence examine it in a cross-sectional setup. In order to maximize the size of our sample, we include all countries that have billionaires in any of the four years considered and we average the value of wealth inequality (and its components) across the four years. We find that while politically connected wealth inequality is correlated with the wheat-sugar ratio with a correlation coefficient of −0.425 (p-value = 0.010), neither wealth inequality nor politically unconnected wealth inequality are correlated with the wheat-sugar ratio (Correlation coefficients are −0.148 and 0.118 respectively with p-values of 0.382 and 0.486).

[27] The LWHEATSUGAR ratio is defined by Easterly (2007) as LWHEATSUGAR=log [(1+share of arable land suitable for wheat)/(1+share of arable land suitable for sugarcane)]. Easterly uses data from the FAO about the percent of national arable land area suitable for different crops, taking into account such factors as soil, rainfall, temperature, and elevation.



Note: Only countries which have billionaires on the Forbes' list are included in this set of graphs. Politically Unconnected Wealth Inequality is politically unconnected billionaire wealth, divided by GDP and Politically Connected Wealth Inequality is politically connected billionaire wealth, divided by GDP.

Fig. 1. Patterns of correlation between components of wealth inequality for 1987, 1992, 1997, and 2002.

As may be seen from the analysis above, politically connected wealth inequality bears a statistically significant relationship with LWHEATSUGAR, whereas wealth inequality and politically unconnected wealth inequality do not. The negative correlation between LWHEATSUGAR and politically connected wealth inequality indicates that countries that have a higher proportion of land exogenously suitable for wheat relative to sugarcane (and which have relatively lower levels of structural inequality) are associated with lower levels of politically connected wealth inequality. Conversely, countries where more land is suitable for growing sugarcane than growing wheat are characterized by a higher level of structural inequality and are also associated with higher levels of politically connected wealth inequality. Overall, the results above offer suggestive evidence that politically connected wealth inequality maps onto Easterly's structural inequality, whereas wealth inequality and politically unconnected wealth inequality encompass both market-based and structural inequality and do not bear a statistically significant relationship with the instrument developed in Easterly (2007).

The results in Table 4 and the above analysis also suggest that our two components of wealth inequality are not strongly correlated with each other. A graph showing the patterns of correlation between these two components of wealth inequality for each year individually for those countries that have billionaires is provided in Fig. 1. The lack of correlation between the two components of wealth inequality is evident from the figure and confirmed from the correlation coefficients of −0.2324, −0.1814, 0.0098, and −0.0661 for 1987, 1992, 1996, and 2002, respectively. In addition, the list of countries with the five highest levels of politically unconnected wealth inequality is completely disjoint from the list of countries with the five highest levels of politically connected wealth inequality.[28] The lack of high correlation between the two variables also permits us to include them simultaneously in the same regression.

[28] The countries with the highest level of politically unconnected wealth inequality are Hong Kong, Philippines, Singapore, Kuwait, and Switzerland, whereas the countries with the highest level of politically connected wealth inequality are Malaysia, Colombia, Indonesia, Thailand, and Mexico.

Table 5
Impact of wealth inequality and its components, income inequality, and headcount poverty on economic growth.

	Dependent variable: Growth rate in real GDP per capita					
	(1)	(2)	(3)	(4)	(5)	(6)
Wealth inequality	−0.132*	−0.547	−50.07***			
	(0.0771)	(0.351)	(13.27)			
Politically unconnected wealth inequality				−0.0464	−0.154	−48.98
				(0.0714)	(0.301)	(36.52)
Politically connected wealth inequality				−0.331***	−1.625***	−51.01**
				(0.0965)	(0.536)	(22.79)
Income inequality	0.000564	0.000763*	0.000498	0.000530	0.000753	0.000498
	(0.000422)	(0.000455)	(0.000417)	(0.000426)	(0.000456)	(0.000418)
Headcount poverty	0.000301	0.000252	0.000353	0.000298	0.000243	0.000352
	(0.000296)	(0.000307)	(0.000286)	(0.000298)	(0.000310)	(0.000297)
Income	−0.0836***	−0.0854***	−0.0813***	−0.0792***	−0.0818***	−0.0812***
	(0.0288)	(0.0302)	(0.0285)	(0.0291)	(0.0304)	(0.0286)
Female schooling	0.00580	0.00716	0.0111	0.0129	0.0137	0.0112
	(0.0225)	(0.0238)	(0.0214)	(0.0215)	(0.0228)	(0.0220)
Male schooling	0.00301	−0.00155	0.00462	0.00202	−0.00218	0.00459
	(0.0227)	(0.0240)	(0.0222)	(0.0220)	(0.0234)	(0.0221)
Price level of investment	−0.0807**	−0.0848**	−0.0695*	−0.0802*	−0.0834*	−0.0697*
	(0.0398)	(0.0403)	(0.0384)	(0.0422)	(0.0419)	(0.0388)
Country on List dummy	−0.00382	−0.00467	−0.00420	−0.00567	−0.00606	−0.00428
	(0.00853)	(0.00867)	(0.00749)	(0.00849)	(0.00864)	(0.00878)
Constant	0.634**	0.648**	0.610**	0.597**	0.616**	0.609**
	(0.241)	(0.254)	(0.239)	(0.243)	(0.255)	(0.239)
Number of observations	160	149	160	160	149	160
R2	0.59	0.59	0.61	0.60	0.60	0.61
F	28.39	21.54	29.68	33.99	23.70	33.06

Growth Rate is the average annual compounded growth rate over a five-year period of Gross Domestic Product per capita in constant prices and expressed in national currency; Income is the log of Real GDP per capita in International dollars in 2000 constant prices; Female (Male) Schooling is the average years of secondary schooling in the female (male) population aged 25 and above; PPPI is price level of investment, measured as the PPP of investment/exchange rate relative to the USA (rescaled here by dividing by 1000); Wealth Inequality is Billionaire wealth, divided by GDP (column (1)), physical capital stock (column (2)), and population (column (3)). Politically Unconnected (Connected) Wealth Inequality is Politically unconnected (connected) billionaire wealth, divided by GDP (column (4)), physical capital stock (column (5)), and population (column (6)). Measures of billionaire wealth are based on Forbes' billionaire lists for 1987, 1992, 1996, and 2002 along with author calculations. Country on List Dummy = 1 if a country has billionaires in a given year, 0 otherwise and is also based on author calculations. Columns (2) and (5) are estimated using observations for which the capital to GDP ratio is between 2.58 and 14.43, corresponding to the 5th and 95th percentile values of the distribution of capital to GDP.
A list of countries included in this estimation are: Algeria, Bangladesh, Bolivia, Botswana, Brazil, Burundi, Cameroon, Central African Republic, Chile, China, Colombia, Costa Rica, Dominican Republic, Ecuador, Egypt, El Salvador, Fiji, Gambia, Ghana, Guatemala, Haiti, Honduras, Hungary, India, Indonesia, Iran, Jamaica, Jordan, Kenya, Lesotho, Malawi, Malaysia, Mali, Mauritania, Mexico, Mozambique, Nepal, Nicaragua, Niger, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Rwanda, Senegal, Sierra Leone, South Africa, Sri Lanka, Swaziland, Thailand, Trinidad and Tobago, Tunisia, Turkey, Uganda, Venezuela, and Zambia.
All regressions include country and period fixed effects. Robust standard errors, clustered by country, in parentheses
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

5. Empirical results

In Section 5.1, we present the results from our base specification – a fixed effects model with lagged values of the explanatory variables in which billionaire wealth is normalized by GDP, physical capital stock, and population, respectively. In Section 5.2, we examine why our results differ from those obtained by Ravallion (2012) and Forbes (2000). Finally, in Section 5.3 we summarize the results of a number of robustness checks.

5.1. Base specification

In Table 5, we report the estimates of Eq. (1), with wealth inequality, income inequality, and initial poverty being the key explanatory variables. The data are from countries reporting some incidence of poverty as measured by $2 per day. The Hausman test indicates that the fixed effects specification is more appropriate than the random effects specification in each case and in Table 5 we therefore report the fixed effects estimates.[29] Estimates from the random effects specification yield similar results and they are reported in Table 8 as part of our robustness checks.

In column (1) of Table 5 we present results from the specification in which wealth inequality is defined as billionaire wealth divided by GDP, while estimates in columns (2) and (3) come from specifications where wealth inequality is defined as billionaire wealth divided by the country's physical capital stock and population, respectively.

[29] For example, for column (1), $\chi 2 = 99.06$, and Probability $> \chi 2 = 0.0000$.

As may be seen from columns (1)–(3), the relationship between wealth inequality and economic growth is negative and significant at the 10% significance test level when billionaire wealth is divided by GDP, negative and significant at the 1% significance test level when billionaire wealth is divided by population, and negative with a *p*-value of 0.121 when billionaire wealth is divided by physical capital stock. The effect of income inequality on growth is positive but statistically insignificant when billionaire wealth is divided by GDP or population, and it is positive and significant at the 10% significance test level when billionaire wealth is divided by physical capital stock. The effect of poverty is insignificant in all three specifications. Our base estimates hence suggest that when all three key regressors are included in the equation, wealth inequality is systematically the most significant determinant of economic growth. Income inequality is of relatively marginal significance, while poverty is not statistically significant in any of the runs.

In columns (4)–(6) of Table 5, we report estimates from the specification where politically unconnected and politically connected billionaire wealth inequality are entered as two separate explanatory variables, along with income inequality and poverty. The results indicate that in all three specifications it is politically connected wealth inequality and economic growth that have a significant negative relationship while politically unconnected wealth inequality does not have such a relationship. The estimated effects of both income inequality and poverty are insignificant in all three specifications. These results hence suggest that it is important to distinguish the nature of wealth inequality in drawing inferences about the effect of wealth inequality on growth and they highlight the negative effect of politically connected wealth inequality in comparison to the insignificant impact of politically unconnected wealth inequality. Moreover, they strengthen our earlier finding that income inequality and poverty are not significant determinants of growth.

In terms of the economic significance of the estimated impact of wealth inequality, note that the –0.132 coefficient on wealth inequality in column (1) implies that a one standard deviation (3.72%) increase in the level of wealth inequality would result in a 0.49% decrease in real GDP per capita growth. This is similar to the 0.6% estimate by Perotti (1996) and somewhat smaller than the 0.8% effect reported by Alesina and Rodrik (1994), with both of these studies using income inequality as a proxy for wealth inequality and examining the relationship in a cross-country cross-sectional framework. Using the estimates in column (4) of Table 5, one can show that a one standard deviation increase in the level of politically connected wealth inequality, holding constant the level of politically unconnected wealth inequality, results in a 0.60% slowdown in per capita GDP growth. Given that the mean per capita GDP growth over the period 1987–2007 was 1.9%, this slowdown of 0.60% represents nearly a third of the average growth rate in GDP per capita. The negative relationship between politically connected wealth inequality and growth is hence quite sizable.

The estimated effects of the control variables are in line with what has been reported elsewhere in the literature. The effect of initial income is negative and significant at the 1% test level, thus providing support for the conditional convergence hypothesis that countries relatively close to their steady-state output level will experience a slower rate of growth. The coefficient on the price level of investment is also negative as is common. The coefficient on the variables corresponding to male and female schooling is positive but not significant. These coefficients are similar to those found in other growth models estimated using the same technique (e.g., Caselli et al., 1996).

5.2. Reconciling our results with those of Ravallion (2012) and Forbes (2000)

In order to gain an understanding of what causes the difference between our results in Table 5 and those of Ravallion (2012), who reports a negative and significant effect of poverty on growth together with an insignificant effect of income inequality on growth, we next re-estimate our equations without wealth inequality as an explanatory variable. As may be seen in column (1) of Table 6, we find that the effect of poverty on growth is still insignificant. Moreover, it remains insignificant even when we exclude both wealth and income inequality as explanatory variables (column (2) of Table 6). The insignificant effect of poverty also obtains in most random effects and most OLS estimations (not reported here), and in some of these estimations (including column (5) of Table 6) the effect of poverty on growth is actually positive. The difference in our and Ravallion's (2012) findings is striking and we conjecture that it stems from the fact that he uses primarily a cross-sectional OLS approach, while we, like Forbes (2000), use primarily panel data with country fixed effects.[30]

We next examine why our estimates may differ from those of Forbes (2000), who reports a positive and statistically highly significant effect of income inequality on growth. As may be seen from column (1) of Table 6, when we re-estimate our equations without wealth inequality as an explanatory variable, we find that the effect of income inequality on growth is statistically insignificant. An insignificant effect of income inequality on growth is also found when both wealth inequality and poverty are excluded as explanatory variables in column (3) of the table. Hence, the inclusion or exclusion of additional explanatory variables, relative to those used by Forbes (2000), does not affect the significance of the coefficient on income inequality. Coefficients (4)–(6) replicate the results of specifications of columns (1)–(3) but use country random effects instead of country-specific fixed effects.

We next check whether the difference between our and Forbes' (2000) results is brought about by the choice of countries. We exclude poverty and re-estimate our equations on the subset of countries used by Forbes (2000). The estimates, reported in Panel A of Table 7 show that our three measures of wealth inequality have a negative effect that is statistically significant at the

[30] Recall that Ravallion (2012) finds that his estimates continue to be statistically significant in the GMM model. However, his estimated negative effect of poverty on growth becomes insignificant when he switches from an OLS to fixed effects estimation.

Table 6
Impact of income inequality and/or headcount poverty on economic growth, without controlling for measures of wealth inequality.

	Dependent variable: Growth rate in real GDP per capita					
	(1)	(2)	(3)	(4)	(5)	(6)
Income inequality	0.000579		0.000302	−0.000175		−0.000289
	(0.000435)		(0.000399)	(0.000448)		(0.000317)
Headcount poverty	0.000292	0.000377		0.000323	0.000277**	
	(0.000306)	(0.000232)		(0.000220)	(0.000134)	
Income	−0.0877***	−0.0626***	−0.0944***	0.00320	0.00709	−0.00456
	(0.0306)	(0.0169)	(0.0239)	(0.00823)	(0.00467)	(0.00405)
Female schooling	−0.00280	−0.00641	−0.00401	−0.00356	−0.00168	−0.00610
	(0.0244)	(0.0203)	(0.0146)	(0.0140)	(0.00864)	(0.00672)
Male schooling	0.00440	0.0130	0.00663	0.0167*	0.0152**	0.00976
	(0.0239)	(0.0149)	(0.0137)	(0.00946)	(0.00704)	(0.00620)
Price level of investment	−0.0972**	−0.0328	−0.0941**	−0.0738	−0.0519	−0.107
	(0.0369)	(0.0270)	(0.0365)	(0.0997)	(0.0342)	(0.0917)
Constant	0.672**	0.477***	0.820***	−0.0311	−0.0710*	0.0669*
	(0.255)	(0.139)	(0.212)	(0.0677)	(0.0420)	(0.0372)
Econometric technique	Fixed effects			Random effects		
Number of observations	160	258	265	160	258	265
R2	0.56	0.41	0.46	0.28	0.22	0.16

The measure of income inequality used is the Gini coefficient of any quality level, ranging from 1 to 4, that is based on either the person or the household as the unit of analysis. Data on income inequality is drawn from the UNU-WIDER World Income Inequality Database 2004.
All regressions include period fixed effects. Regressions in columns (1) – (3) use country-specific fixed effects, whereas regressions in columns (4) – (6) use random effects.
For complete notes, please refer to Table 5.
Robust standard errors, clustered by country, in parentheses
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

1% test level, while the effect of income inequality is positive but statistically insignificant. The use of Forbes' (2000) sample of countries hence does not materially affect the impact of wealth inequality, but it does not generate the positive effect of income inequality identified by Forbes (2000).

We next explore whether the difference in the time period covered by Forbes (2000) and our study (1965–1995 *vs.* 1987–2007) could explain the difference in our and Forbes' (2000) estimates. In order to do so, we use the same subset of countries as Forbes (2000) but allow the effects of wealth and income inequality to vary between the 1987–1997 and 1997–2007 periods. The estimated coefficients, reported in Panel B of Table 7 show that the effects of our three measures of wealth inequality are negative in the second period and since the differences in these effects between the second and first period are not statistically significant, they are negative and significant in the entire 1987–2007 period. The estimated effect of income inequality is insignificant in the second period, but the coefficient on income inequality interacted with the dummy variable for the first period (1987–1997) is positive and statistically significant in the specification where wealth inequality is excluded. These results are hence consistent with Forbes' (2000) finding that the effect of income inequality was positive in 1987–1997 (the part of our sample period that overlaps with that of Forbes, 2000) when wealth inequality was not included as a regressor. That pattern is reaffirmed when we look at the estimated coefficients from the full model reported in columns (2)–(4) of Panel B of Table 7. The coefficient on income inequality is generally significant in these specifications in the first (1987–1997) period, and it becomes insignificant thereafter.

Our estimates in Tables 6 and 7 hence support the conclusion we drew earlier that wealth inequality and economic growth have a negative relationship. Moreover, we find that the effect of initial poverty is statistically insignificant irrespective of whether wealth inequality is included or excluded as a regressor as long as the variable is introduced in a panel set-up with country fixed or random effects – a likely reason why our estimated effect of poverty differs from the negative OLS estimate of Ravallion (2012). Finally, we are able to replicate Forbes' (2000) positive effect of income inequality on growth in the early (1987–1997) period when wealth inequality is excluded, but we show that the effect becomes less robust when wealth inequality is included. Interestingly, the effect of income inequality becomes insignificant in the post-1997 period, suggesting that wealth rather than income inequality has started to play an increasingly important part. It is worth noting that our results are consistent with those of Deininger and Olinto (2000) who include land inequality (their proxy for wealth inequality) and income inequality in the same specification in a panel setup. They find that the coefficient on land inequality is negative and significant, while the coefficient on income inequality is positive and occasionally significant.

Table 7
Impact of income inequality and wealth inequality on economic growth, estimated on same set of countries as in Forbes (2000).

	Dependent variable: Growth rate in real GDP per capita			
	(1)	(2)	(3)	(4)
Panel A: Assuming income and wealth inequality to have the same effect during the entire sample period				
Income inequality	0.000751	0.000991	0.00102	0.000947
	(0.000886)	(0.000830)	(0.000858)	(0.000840)
Wealth inequality		−0.154***		
(GDP used for normalization)		(0.0484)		
Wealth inequality			−0.578***	
(Physical capital used for normalization)			(0.179)	
Wealth inequality				−6.255***
(Population used for normalization)				(2.061)
Number of observations	162	162	152	162
R2	0.39	0.45	0.44	0.42
F	5.343	8.717	8.740	7.138
Panel B: Allowing for the effects of inequality to differ between the first and second half of the sample periods				
Income inequality	0.000419	0.000757	0.000698	0.000630
	(0.000894)	(0.000858)	(0.000896)	(0.000847)
Wealth inequality		−0.131**		
(GDP used for normalization)		(0.0493)		
Wealth inequality			−0.525**	
(Physical capital used for normalization)			(0.201)	
Wealth inequality				−7.771***
(Population used for normalization)				(2.690)
Income inequality interacted with “First half of sample period” dummy	0.000750**	0.000492	0.000653*	0.000742**
	(0.000327)	(0.000333)	(0.000344)	(0.000317)
Wealth inequality interacted with “First half of sample period” dummy (GDP used for normalization)		0.0691		
		(0.0797)		
Wealth inequality interacted with “First half of sample period” dummy (Physical capital used for normalization)			0.0150	
			(0.346)	
Wealth inequality interacted with “First half of sample period” dummy (Population used for normalization)				−6.665
				(5.169)
“First half of sample period” dummy	−0.0742***	−0.0640***	−0.0465***	−0.0738***
	(0.0182)	(0.0181)	(0.0151)	(0.0173)
Number of observations	162	162	152	162
R^2	0.41	0.46	0.46	0.46
F	4.720	9.321	9.280	6.751

“First half of sample period” dummy is set to 1 for the years 1987–1992 and 1992–1997. The measure of income inequality used is the Gini coefficient of any quality level, based on either the person or household as the unit of analysis. Column (3) is estimated using observations for which the capital to GDP ratio is between 2.58 and 14.43, corresponding to the 5th and 95th percentile values of the distribution of capital to GDP.
This regression is estimated only on the sample of countries included in Forbes (2000): Australia, Bangladesh, Belgium, Brazil, Bulgaria, Canada, Chile, China, Colombia, Costa Rica, Denmark, Domini- can Republic, Finland, France, Germany, Greece, Hong Kong, Hungary, India, Indonesia, Ireland, Italy, Japan, Malaysia, Mexico, Netherlands, New Zealand, Norway, Pakistan, Peru, Philippines, Poland, Portugal, Republic of Korea, Singapore, Spain, Sri Lanka, Sweden, Thailand, Trinidad and Tobago, Tunisia, Turkey, United Kingdom, United States, and Venezuela.
All regressions include male and female years of schooling, the price level of investment, country and period fixed effects. For complete notes, please refer to Table 5.
Robust standard errors, clustered by country, in parentheses

* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

5.3. Additional robustness checks

In this section we report the results of additional robustness checks and show that the results for the base specification presented in Section 5.1 hold up. In order to conserve space, in Table 8 we report estimated coefficients for the wealth inequality variable (or its components) from the various regressions corresponding to specific robustness checks without including coefficients on the other control variables. Full results are available from the authors on request.

(a) RC1*: Robustness to Forbes magazine's choice of countries for the billionaires in the data set:* As described in Data Appendix A1, in a total of 30 (less than 2%) of the 1652 entries we assign a person a different country than what was assigned to him by Forbes magazine. We examine the robustness of our results to Forbes magazine's assignment of country and find that the results remain essentially unchanged.
(b) RC2*: Use of alternative econometric approaches:*

Table 8
Sensitivity to alternative specifications of the coefficient on wealth inequality (columns (1)–(3)), or its two components when introduced simultaneously (columns (4)–(9)).

	Dependent variable: Growth rate in real GDP per capita[a]								
	(1) Coefficient on wealth inequality -normalized by	(2)	(3)	(4) Coefficient on politically unconnected wealth inequality - normalized by	(5)	(6)	(7) Coefficient on politically connected wealth inequality - normalized by	(8)	(9)
	GDP	Physical capital stock	Population	GDP	Physical capital stock	Population	GDP	Physical capital stock	Population
Base specification	−0.132*	−0.547	−50.07***	−0.0464	−0.154	−48.98	−0.331***	−1.625***	−51.01**
	(0.0771)	(0.351)	(13.27)	(0.0714)	(0.301)	(36.52)	(0.0965)	(0.536)	(22.79)
Robustness to Forbes' magazine's assignment of billionaires to the various countries (RC1)	−0.132*	−0.546	−50.07***	−0.0454	−0.152	−49.07	−0.332***	−1.626***	−50.93**
	(0.0768)	(0.350)	(13.25)	(0.0709)	(0.300)	(36.50)	(0.0965)	(0.536)	(22.82)
Use of alternative econometric approaches (RC2)									
(i) Use of random effects (RE) specification	−0.162*	−0.652	−59.05***	−0.0145	0.0261	−17.52	−0.458***	−2.332***	−90.14***
	(0.0962)	(0.431)	(14.67)	(0.0688)	(0.284)	(48.52)	(0.0600)	(0.409)	(20.85)
(ii) Use of Blundell-Bond system-GMM estimator	−0.593*	−2.135	−210.9***	−0.277	−0.564	−183.6	−1.405*	−6.699*	−236.7
	(0.355)	(1.439)	(57.86)	(0.475)	(1.589)	(332.7)	(0.782)	(3.589)	(266.0)
(iii) Use of Arellano-Bond difference-GMM estimator	−0.498*	−2.059	−167.3**	−0.112	−0.437	−126.2	−1.514**	−6.960*	−202.2
	(0.292)	(1.263)	(66.25)	(0.220)	(0.969)	(174.7)	(0.720)	(3.854)	(149.4)
Inclusion of additional control variables (RC3)									
(i) Institutional quality	−0.142*	−0.596*	−51.64***	−0.0581	−0.207	−56.33	−0.334***	−1.660***	−47.59**
(Economic Freedom Index)	(0.0768)	(0.349)	(13.36)	(0.0725)	(0.297)	(35.00)	(0.0983)	(0.557)	(22.14)
(ii) Exchange rate	−0.137*	−0.570	−51.53***	−0.0516	−0.175	−52.23	−0.334***	−1.653***	−50.93**
(including all observations)	(0.0792)	(0.363)	(13.72)	(0.0751)	(0.318)	(38.59)	(0.0964)	(0.538)	(23.10)
Using $1.25 per day per person as the poverty line (RC4)	−0.131*	−0.542	−49.40***	−0.0449	−0.148	−47.27	−0.330***	−1.624***	−51.24**
	(0.0758)	(0.347)	(13.29)	(0.0698)	(0.296)	(37.17)	(0.0970)	(0.533)	(22.97)

All regressions, except otherwise specified in the text, include income inequality, headcount poverty, initial income, male and female secondary years of schooling, PPPI, and country and period fixed effects. The number of observations varies based on the robustness check employed. For RC 2(ii) and (iii), the coefficients obtained with the system-GMM and difference-GMM estimators are not directly comparable with the coefficients obtained in the other regressions because of the difference in the dependent variables. In RC3(i), the measure of Institutional Quality, the Economic Freedom Index is sourced from the Fraser Institute (Gwartney, Hall, and Lawson, 2011). Also, in RC3(ii), the exchange rate is sourced from the Penn World Tables v6.2. Columns (1)–(3) each correspond to a different regression. Columns (4) and (7) come from the same regression run. Likewise, columns (5) and (8) & (6) and (9). Coefficients in columns (4) and (7) should be read together. Likewise, columns (5) and (8) & (6) and (9).
Full results are available on request. For complete notes, please refer to Table 5.
Robust standard errors, clustered by country, in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.
[a] For the Blundell-Bond system-GMM and Arellano-Bond difference-GMM estimators, the dependent variable is log of Real GDP per capita.

(i) Use of a random effects instead of a fixed effects specification: Our use of the country fixed effects model is justified by the results of the Hausman test. In all cases, the Hausman test rejects the null hypothesis of no correlation between the unobserved country-specific random effects and the explanatory variables, implying that random effects estimates are biased and inconsistent. However, we have also estimated the random effects specification as Griliches and Hausman (1986) stress that observing similar estimates across alternative panel data estimation techniques signals the absence of serious errors-in-variables problems. Using the random effects specification, we find the wealth inequality has a negative and generally statistically significant effect on growth at the 10% level in the first specification, 13% level in the second, and 1% level in the third specification. Similarly, politically connected wealth inequality has a coefficient that is negative and statistically significant at the 5% level (or better) in all three specifications. Politically unconnected wealth inequality continues to be statistically insignificant all throughout.

(ii) Using instrumental variables: Finding valid IVs in a non-experimental setting is obviously difficult. We have, in the end, found two IVs that satisfy the formal statistical test criteria, although they have conceptual weaknesses. They yield similar results as the other methods that we use. The first IV strategy relies on decomposing billionaire wealth normalized by GDP into the product of average billionaire wealth divided by per capita income and the number of billionaires divided by population. It is motivated by the fact that the average billionaire wealth in any given country is strongly correlated with the contemporaneous average billionaire wealth in the region to which a country belongs.[31]

[31] The world was divided into five regions: The Americas (excluding North America), Asia, Europe, Middle East & Africa, and North America (including Canada, Mexico, and the U.S.).

Beyond its association with average billionaire wealth of a country, one may argue that the average billionaire wealth in other countries in the same region does not affect a country's economic growth. On this basis one can use average regional billionaire wealth, excluding the own country, as an instrument for own-country billionaire wealth.

The other IV that we have used is the exchange rate. This choice may be motivated by the fact that Forbes magazine only includes people on the list if their wealth is in excess of $1 billion when expressed in USD. One can therefore use the exchange rate as an IV under the assumption that it affects measured wealth inequality but does not affect growth through other means. We obtain estimates that are very similar to what we found using regional average billionaire wealth. The results using either IV approach are available from the authors on request.

(iii) Using dynamic panel methods of estimation: In the absence of suitable instruments that satisfy both the validity and exclusion restrictions, we turn to the system-GMM estimator following others in the literature (e.g. Hausman, Hwang, and Rodrik, 2007; Marrero and Rodríguez, 2013; and Rajan and Subramanian, 2008). The system-GMM estimator approach is based on the use of internal instruments (lagged levels and lagged differences) and estimates a system of equations in both first-differences and levels. We use the estimator developed by Blundell and Bond (1998) and find that in two of the three specifications in which wealth inequality is introduced, it is significant at the 10% level (or better) and in the third specification, it falls short of statistical significance with a p-value of 0.138. When we introduce the two components of wealth inequality separately in the regressions, we find that politically connected wealth inequality is statistically significant at the 10% level in two of the three specifications whereas politically unconnected wealth inequality is statistically insignificant in all three specifications.

We use the one-step system-GMM estimator with robust standard errors as these standard errors are robust to heteroskedasticity and are more reliable for finite sample inference compared to the two-step variant (Blundell and Bond, 1998; Bond et al., 2001; and Marrero and Rodríguez, 2013). One potential issue with the use of the system-GMM estimator is that the Sargan test of overidentifying restrictions is rejected raising questions about the validity of the instrument set. Given that, we also use the Arellano and Bond (1991) difference-GMM estimator to examine the robustness of the relationship between economic growth and wealth inequality, income inequality, and headcount poverty. The pattern of results is identical to that obtained using the system-GMM estimator and confirm the key findings of the paper. In addition, the Sargan test of overidentifying restrictions is not rejected for the difference-GMM estimator suggesting the validity of the instruments used.

(c) RC3*: Robustness to inclusion of additional explanatory variables*

(i) Adding a measure of institutional quality: The inclusion of country fixed effects deals with the problem of omitted variable bias in that all country-specific factors that are invariant over time (e.g., a country's legal origin) are controlled for by the country fixed effect. However, the fixed effects specification does not deal with country-specific factors that may vary over time. Given the importance that the literature assigns to institutional quality (e.g., Rodrik, Subramanian, and Trebbi, 2004), we examine the robustness of our results to the inclusion of a measure of institutional quality. We employ the very widely used Economic Freedom Index constructed by the Fraser Institute and we find that controlling for this aggregate measure of institutional quality does not alter any of the findings of our paper.

(ii) Controlling for the exchange rate: The Forbes' billionaire list converts wealth in local currency into U.S. dollars using the current exchange rates. Fluctuations in the exchange rates thereby induce a variation in the measure of wealth inequality even when the true underlying level of wealth inequality in the country is unchanged. We examine the robustness of our results to inclusion of the exchange rate as a control. We also re-estimate the regression only on those observations for which the variation in the exchange rate from one period to the next is within 5%–95% of the distribution of change in exchange rates. In both cases, we find that our basic results continue to hold and are robust to the inclusion of the exchange rate control.

(d) RC4*: Using $1.25 per day per person as the poverty line:* Thus far we have used a headcount measure of poverty based on the fraction of individuals consuming less than $2 per person per day, as used by Ravallion (2012). In addition, like him, we also consider for robustness a lower consumption threshold of $1.25 per day per person which is the expected value of the poverty line in the poorest countries. The results obtained with such a threshold are very similar to those obtained previously.

5.3.1. Robustness to sample selection issues

Our measure of wealth inequality relies on the presence of billionaires (with wealth measured in USD) on Forbes' annual lists of billionaires. In the process, we impute a value of zero to the level of wealth inequality for those countries which do not have any billionaires. This could be problematic either because data are incomplete or because they are missing for many smaller countries with weak institutions and high levels of tax evasion and/or fuzzy accounting. Thus, even if some rich people in some countries are not classified as billionaires by the Forbes magazine, it does not mean that wealth inequality is not acute in those countries.

We consider the inability to construct measures of wealth inequality that are not zero for countries of the world which do not have billionaires as a limitation of our analysis and agree that there may be an element of sample selection in generating our measure of wealth inequality. However, we are unable to address that potential concern by estimating the regressions only on the sample of countries that are included on the Forbes' lists without making any other revisions for the reasons described here. The independent variable, headcount poverty, is defined as the proportion of the population living in households with

Table 9
Impact of wealth inequality and its components, income inequality, and headcount poverty on economic growth, estimated only on countries which have billionaires at least once.

	Dependent variable: Growth rate in real GDP per capita					
	(1)	(2)	(3)	(4)	(5)	(6)
Wealth inequality	−0.102*	−0.343*	−3.591**			
	(0.0514)	(0.183)	(1.727)			
Politically unconnected wealth inequality				−0.0754	−0.254	−3.414**
				(0.0461)	(0.153)	(1.570)
Politically connected wealth inequality				−0.203**	−1.019**	−37.06**
				(0.0910)	(0.496)	(18.20)
Income inequality	0.00123	0.00122	0.00122	0.00120	0.00119	0.00114
	(0.000817)	(0.000860)	(0.000832)	(0.000833)	(0.000874)	(0.000837)
Headcount poverty	−0.000248	−0.000198	−0.000211	−0.000249	−0.000199	−0.000169
	(0.000455)	(0.000460)	(0.000436)	(0.000451)	(0.000459)	(0.000431)
Income	−0.0929***	−0.0890**	−0.0926**	−0.0899**	−0.0858**	−0.0880**
	(0.0336)	(0.0368)	(0.0345)	(0.0347)	(0.0379)	(0.0358)
Female schooling	−0.0124	−0.0138	−0.0143	−0.00846	−0.00948	−0.00996
	(0.0173)	(0.0189)	(0.0176)	(0.0175)	(0.0191)	(0.0174)
Male schooling	0.0173	0.0168	0.0181	0.0138	0.0132	0.0154
	(0.0177)	(0.0190)	(0.0177)	(0.0179)	(0.0194)	(0.0177)
Price level of investment	−0.177	−0.142	−0.195	−0.198	−0.169	−0.193
	(0.146)	(0.192)	(0.143)	(0.142)	(0.193)	(0.144)
Country on list dummy	−0.00561	−0.00702	−0.00873*	−0.00530	−0.00624	−0.00766
	(0.00466)	(0.00526)	(0.00442)	(0.00479)	(0.00557)	(0.00468)
Constant	0.839**	0.800**	0.840**	0.814**	0.775**	0.797**
	(0.334)	(0.363)	(0.342)	(0.343)	(0.371)	(0.352)
Number of observations	134	124	134	134	124	134
R2	0.52	0.51	0.50	0.52	0.51	0.51
F	16.55	12.52	8.477	21.82	23.88	19.80

Growth Rate is the average annual compounded growth rate over a five-year period of Gross Domestic Product per capita in constant prices and expressed in national currency; Income is the log of Real GDP per capita in International dollars in 2000 constant prices; Female (Male) Schooling is the average years of secondary schooling in the female (male) population aged 25 and above; PPPI is price level of investment, measured as the PPP of investment/exchange rate relative to the USA (rescaled here by dividing by 1000); Wealth Inequality is Billionaire wealth, divided by GDP (column (1)), physical capital stock (column (2)), and population (column (3)). Politically Unconnected (Connected) Wealth Inequality is Politically unconnected (connected) billionaire wealth, divided by GDP (column (4)), physical capital stock (column (5)), and population (column (6)). Measures of billionaire wealth are based on Forbes' billionaire lists for 1987, 1992, 1996, and 2002 along with author calculations. Country on List Dummy = 1 if a country has billionaires in a given year, 0 otherwise and is also based on author calculations. Columns (2) and (5) are estimated using observations for which the capital to GDP ratio is between 2.58 and 14.43, corresponding to the 5th and 95th percentile values of the distribution of capital to GDP. Headcount poverty as obtained from the World Bank's PovCalNet tool has been augmented by setting it to zero for all observations for which GDP per capita exceeds $12,523.

All regressions include country and period fixed effects. Robust standard errors, clustered by country, in parentheses

* $p < 0.10$.

** $p < 0.05$.

*** $p < 0.01$.

consumption per capita less than $2 per person per day at 2005 PPP and is directly sourced from the World Bank's PovcalNet tool. This measure of poverty is unavailable for much of the developed world.[32] Therefore to include country-period observations only for countries that have billionaires, we would have to limit ourselves to country-period observations with billionaires that also have enough people consuming less than $2 per person per day for the World Bank poverty statistics to exist. Those criteria are simultaneously satisfied for only 39 country-period observations which correspond to 15 countries.[33] The small sample size obtained by including all independent variables, limiting ourselves to only countries which have billionaires, and not imputing a value of headcount poverty makes it not very meaningful to estimate our regressions on this greatly reduced sample.

We therefore address this concern in two ways: First, we impute a value of headcount poverty = 0 for all countries for which the per capita income exceeds $12,523, as this income corresponds to the highest income level for any country-period observation for which the level of headcount poverty is positive. Implicitly the assumption is that for all countries for which income exceeds $12,523 per capita, the level of headcount poverty, as defined by the $2 per day measure, is zero. This is a reasonable assumption as some of the country-period observations to the right of the threshold of $12,523 are: Spain (all years), Portugal (1992, 1997, and 2002), and Israel (all years): countries for which we feel confident in asserting that there were no individuals consuming less than the equivalent of $2 a day. The regression results with this imputation estimated only on those sample of countries that show up at least once in the Forbes' billionaire lists are presented in columns (1)–(3) of Table 9. Subsequent columns of Table 9 consider the effects of the components of wealth inequality on economic growth.

[32] As the World Bank's documentation notes, "International poverty estimates are available for low and middle-income countries only."

[33] Those 15 countries are Brazil, Chile, China, Colombia, Ecuador, India, Indonesia, Malaysia, Mexico, Peru, Philippines, South Africa, Thailand, Turkey, and Venezuela.

We observe that the levels of statistical significance of our results do not change from those that were reported in the paper. Even though the absolute magnitude of the coefficients differ between the base specifications and those reported in Table 9, the implied effect on economic growth arising from an increase in the level of wealth inequality is similar as the standard deviation for wealth inequality differs between the two samples because of differences in sample composition. In particular, for the specification when billionaire wealth is normalized by population, the estimated effect on economic growth for a one standard deviation increase in the level of wealth inequality is –0.66% in the base specification (column (3) of Table 5) and –0.43% in the sample limited to countries which have billionaires at least once (column (3) of Table 9).[34] Our conclusion that it is politically connected wealth inequality that has a significant negative relationship with growth, while politically unconnected wealth inequality does not is also generally reaffirmed on the basis of results in Table 9. Politically connected wealth inequality is statistically significant at the 5% level in all three specifications whereas politically unconnected wealth inequality is insignificant in two of the three specifications. Income inequality and headcount poverty continue to be insignificant in all three specifications in columns (4)–(6).

Another approach that we adopt towards addressing the concern of sample selection is to drop the independent variable headcount poverty (rather than impute values) and estimate the effects of wealth inequality on growth limiting ourselves to only those countries which show up at least once on the Forbes' billionaire datasets. Such a parsimonious specification focuses on the effect that wealth and income inequality have on economic growth and the control variables included are limited to those in Perotti (1996): lagged GDP per capita, male and female years of schooling, the price level of investment, and country and period fixed effects. The pattern of coefficients obtained with such a specification is similar to that obtained earlier and suggests that wealth inequality has a negative relationship with economic growth. In contrast, income inequality is not statistically significant in these specifications and a pattern suggesting that it does not have a relationship with economic growth is established.

Finally, we also use dynamic methods of panel estimation to examine the robustness of the results to these issues of sample selection. We follow our earlier approach of using the Blundell-Bond one-step estimator with standard errors clustered by country and limit ourselves to only countries which have billionaires at least once.[35] The results from the dynamic panel estimation reaffirm our conclusion that wealth inequality has a negative and statistically significant relationship with economic growth as it is statistically significant at the 5% level in all three specifications.[36] These additional results are available from the authors on request.

6. Concluding remarks

A central question in the social sciences is whether inequality in control over a society's resources facilitates or hinders economic growth. The issue has been intensively studied but is far from settled, in part because theoretical arguments have been largely based on the distribution of wealth, while empirical studies have been forced to use the distribution of income as a proxy. We bridge this gap by deriving the first global measure of wealth inequality, focusing on the concentration of wealth at the very top of the pyramid, and estimating the effect of this wealth inequality on economic growth. In addition, motivated by Ravallion's (2012) recent finding that poverty rather than income inequality determines economic growth, we provide a comparison of the effects of wealth inequality, income inequality, and poverty on growth. Finally, we generate measures of politically connected and politically unconnected wealth inequality and estimate their respective effects on growth.

Our first set of findings suggests that wealth inequality tends to have a negative effect on economic growth, income inequality has no or at most a weak positive effect on growth, and the effect of poverty on growth is insignificant. The reason why the positive growth effect of income inequality found in a leading earlier study (Forbes, 2000) is less statistically significant in our data appears to be brought about by the exclusion of wealth inequality in Forbes' (2000) specification and by weakening of the previously positive growth effect of income inequality from the mid-to-late 1990s on. As to the fact that we find an insignificant effect of poverty on economic growth, we conclude that it stems from the fact that Ravallion (2012) uses primarily a cross-sectional OLS approach, while we, like Forbes (2000), use primarily panel data with fixed effects.

Our second key finding is that when we enter politically connected and unconnected wealth as two separate explanatory variables into our regressions, our estimates suggest that it is politically connected wealth inequality that has a significant negative effect on growth, while the effects of politically unconnected wealth inequality, income inequality, and poverty are all insignificant.

Our finding that it is politically connected rather than politically unconnected wealth that is likely to dampen growth may be illustrated by two country-specific examples. The first example is Mexico's telecom industry where the world's wealthiest individual, Carlos Slim Helu, built his fortune. Comparing prices of residential and business telecommunications in all OECD countries, OECD's (1999) report concluded that "in both cases Mexico's prices are well above the OECD average." OECD (1999)

[34] The coefficient on wealth inequality, when billionaire wealth is normalized by population, is –50.07 in column (3) of Table 5. One standard deviation for this measure of wealth inequality is 0.000132 and hence the estimated effect on economic growth of a one standard deviation increase in the level of wealth inequality = $-50.07 * 0.000132 = -0.66\%$. Likewise, the coefficient on wealth inequality in column (3) of Table 9 when billionaire wealth is normalized by population is –3.591. One standard deviation for this measure of wealth inequality is 0.00121 and hence the estimated effect on economic growth of a one standard deviation increase in the level of wealth inequality = $-3.591 * 0.00121 = -0.43\%$.

[35] This approach, like the first, also requires us to impute a value of headcount poverty = 0 for rich countries, defined as countries with an annual income per capita exceeding $12,523.

[36] Using the Arellano and Bond (1991) difference-GMM estimator, we obtain coefficients that are similar in magnitude as those obtained with the system-GMM estimator but have larger standard errors.

also found that the cost of the basket of telecommunications services used by consumers in Mexico, measured in US dollars using Purchasing Power Parity indices, is about three times that of the OECD. Moreover, Mexican investment in information and communications technologies, a field that is dominated by Carlos Slim Helu's Telmex, was at 3.1% of GDP, lagging developed countries such as Japan at 7.4%, the United States at 8.8%, and even regional peers with healthier competition in telecom such as Chile at 6.7% and Brazil at 6.9% (Winter, 2007). Finally, the high price of telecommunication services coupled with the low levels of investment have resulted in by far the lowest penetration rate of telephones among OECD countries.[37] This is in spite of the fact that Telmex was given the right to charge high access rates to competitors because it was to use the extra income to get more phones to more people (OECD, 1999).

Indonesia's tobacco industry provides another telling example of the effects of political connectedness.[38] The influence of the tobacco industry on government policy is enormous and Indonesia is the only country in Asia to have not signed the WHO Framework Convention on Tobacco Control (WHO FCTC), a treaty that as of September 2013 had been signed by 177 parties, including Iran, North Korea, Syria, and Sudan. The FCTC addresses a number of issues, such as promoting taxation as a way to reduce cigarette consumption, imposing restrictions on smoking in public places, enacting comprehensive bans on tobacco advertising, promotion and sponsorship within five years of ratification, putting larger health warnings on cigarette packs, and intensifying the fight against tobacco smuggling (Wijaya, 2008). Indonesia has not signed the convention in spite of the fact that it is a country in which Muslims constitute approximately 86% of the population and "smoking is either completely prohibited in Islam or abhorrent to such a degree as to be prohibited." (WHO Regional Office for the Eastern Mediterranean). The effect of the tobacco industry on the Indonesian economy is also evident from the fact that Indonesia's average tobacco tax of 37% is the lowest in Southeast Asia and well below the global average of 70% of the sales price (South China Morning Post, 2008).

These and other examples, together with our econometric results, suggest that the policy debate about sources of economic growth ought to focus on the distribution of wealth rather than on the distribution of income. Moreover, particular attention ought to be paid to politically connected concentration of wealth as a possible cause of slower economic growth. Further research in this area is obviously needed, especially with respect to the effects of wealth inequality at different parts of the wealth distribution, the possibly declining effect of unequal distribution of income on growth, and the role of poverty.

Appendix. Data Appendix

A1. Construction of billionaire lists

Forbes Magazine published a list of the four hundred richest individuals in the United States, the so-called Forbes Four Hundred for the first time in 1982. It was then followed by the publication of a list of individuals and families from all countries from around the world having more than $1 billion in wealth (in nominal terms) in 1987. Since then, these lists have been published annually. For all countries of the world but the United States, we exclusively rely on the wealth data provided in the billionaire lists. In the case of the United States only, where additional information is available from the Forbes Four Hundred, we also use the information contained therein and aggregate the wealth of family members whose individual amounts of wealth are below a billion dollars but cumulatively sum up to more than a billion dollars. We add them to the list of billionaires to get an augmented list. This step is necessary in order to make the numbers comparable for the United States over all four years of the sample. All of our results are robust to the exclusion of United States from the sample.

In the vast majority of the cases, the locus of business activities for a billionaire is the same as the person's country of origin and/or his country of birth. However, they do not match up in all cases. When that happens, we depart from Forbes magazine's chosen categorization of country and instead assign him to the country where he presently resides and maintains his business activities. For example, in the case of Stelios Haji-Ionnanou of EasyAir whose business activities are currently based in the U.K. where he spends a considerable fraction of his time, we classify him as British. However considering his Greek origin, Forbes classifies him as Greek. Likewise in the case of Lakshmi Mittal of ArcelorMittal who Forbes classifies as Indian considering that he is of Indian origin, we choose to classify him as British since he moved out of India in the late 1970s and has been settled in London, U.K. since 1995. However such circumstances arise in only 30 of the 1652 entries on our list, or less than 2% of the total number of entries. These 30 billionaires who we categorize against a particular country different from Forbes' initial classification account for less than 2% of the total billionaire wealth and the results we obtain for wealth inequality are robust to whether we go with our choice of a country or with Forbes' magazine original assignment of country.

Finally, Forbes magazine changed its editorial policy for four years, between 1997 and 2000. In these years, they included only those billionaires who were either self-made (e.g., Warren Buffett) or those who inherited their wealth and were actively managing it themselves (e.g., Carlos Slim Helu of Mexico). This leads to the exclusion of billionaires from around the world who simply inherited their wealth and were no longer actively involved themselves in growing their businesses, such as the duPonts and Rockefellers in the U.S., the Quandt family of Germany (the largest shareholder of BMW), and Liliane Bettencourt of France

[37] As OECD (1999) reported, at the start of 1998 Mexico had less than 10 telephones per 100 inhabitants, while Poland, the next worst performer among OECD countries, had 20. Moreover, no new access lines were added in Mexico in 1996 and 1997.

[38] Two of the three richest billionaire entities in Indonesia as of 2012, R. Budi & Michael Hartono and Susilo Wonowidjojo, owe their fortunes to tobacco-related industries (Forbes, 2012).

(the largest shareholder of L'Oreal) to provide a few examples.[39] Thus while the three other years of the panel – 1987, 1992, and 2002 included all categories of billionaires, including those who simply inherited their wealth and were not actively managing it themselves such as those mentioned above, the 1997 list, generally failed to include them by design making it challenging to have the lists comparable across the four years. Given this limitation of the 1997 list, we use the 1996 list instead, assuming that had Forbes chosen to include all billionaires in their 1997 listing, then the measures of wealth inequality and political connections we would have arrived at for 1997 are similar to what we arrive at by looking at the 1996 list. That said, the correlation coefficient between wealth inequality, constructed from the 1996 and 1997 lists is 0.9456 (p-value < 0.0001) and that between politically connected wealth inequality for the two years is 0.9600 (p-value < 0.0001). The regression results obtained by using the 1997 list instead of the 1996 list are similar to those reported in the paper and are available on request.

A2. Countries that appear on the Forbes' billionaire list at least once in the four years – 1987, 1992, 1996, and 2002 and level of wealth inequality in those countries (Table A1)

A3. Classifying billionaires as politically connected or not

The following are three examples of brief news reports that resulted in classification of billionaires as "politically connected."

1. The first example is of an Indonesian magnate, Prajogo Pangestu.
In any case, there is no denying that Indonesian government agencies have helped Mr. Prajogo make the leap from a successful timber merchant to a major corporate force. His Barito Group of companies, for example, is the state banking system's largest borrower, with loans of more than $1 billion outstanding, and benefits from an *unusually attractive 1992 debt rescheduling* [Emphasis added] that stretched repayment periods on about $460 million in timber industry borrowings into the next century. Mr. Prajogo, Mr. Bambang and their partners also stand to gain from a change of government policy last year that allowed them to proceed with their postponed $1.6 billion PT Chandra Asri petrochemical project, the products of which will be protected by *steep new tariffs* [Emphasis added] on imports. (The Wall Street Journal Asia, 1993)
2. We next provide Forbes magazine's description of the Birla family, India's only billionaire entry until 1996:
The nationalists who later became free India's power elite rewarded the Birla family with lucrative contracts. After independence, the Birlas continued their lavish contributions to the ruling Congress Party. So accomplished are they in manipulating the bureaucracy, and so vast their network of intelligence, that they frequently obtain preemptive licenses, *enabling them to lock up exclusive rights for businesses as yet unborn* [Emphasis added] (Forbes, 1987).
3. Finally, the following description pertains to Russian billionaire, Mikhail Fridman who shows up on the Forbes' list in 2002:
Mikhail Fridman founded OAO Alfa Bank in 1991 and soon after recruited Pyotr Aven, former minister of foreign economic relations, to raise Alfa's political profile. The partners were among a handful of businessmen who helped to finance Boris Yeltsin's re-election campaign in 1996. The Kremlin *rewarded* these men by selling them state-owned oil and metals companies at *bargain-basement prices* [Emphasis added] (The Wall Street Journal, 2001).

A4. Ranking of countries with the highest and lowest levels of politically connected billionaire wealth on Transparency International's Corruption Perceptions Index for 1995 and 2012

The following Table A2 offers the rank on Transparency International's Corruption Perceptions Index (CPI) for the six countries with the lowest average level of politically connected wealth inequality which show up in each of the four years of our sample and the five countries with the highest average level of politically connected wealth inequality. Transparency International (TI) was formed in May 1993 but the first CPI was not published until 1995. We report the rank of each country on the CPI for 2012, the last year for which the index is available and 1995. A country that has a higher absolute rank on the index is perceived as more corrupt than a country with a lower absolute rank on the index. For example, Indonesia ranked at 118 in 2012 is perceived as more corrupt than Hong Kong which is ranked at 14 on the index (Table A2).

A5. The effects of clustering standard errors in two dimensions

We have explored the use of appropriate econometric techniques to adjust for clustering standard errors in two dimensions – country and time. The user-written Stata command, "ivreg2" (Baum et al., 2007) was chosen for this purpose. The choice of "ivreg2" is explained by the fact that the standard error of 0.0737 we obtain with it when we cluster by country is close to the standard error of 0.0771 obtained using "xtreg" with country-specific fixed effects and clustering along that dimension.

[39] This is how Forbes described its change in editorial policy in 1997: "Ten years ago Forbes started counting billionaires outside the U.S. We found 96. Last year, 298-plus 149 American billionaires. With stock markets around the world up an average 23% in the last year, the billionaire population, like the deer population, is sure to have increased. Bowing to economic reality, we have revised our selection process this year. A billion bucks no longer gets you in. You have got to have made it yourself, or you have got to be actively managing it. This eliminates a fair number of jet-setters and Palm Beach residents. We have culled the roster of billionaires down to 200 people around the globe, the Global Superrich."

Table A1
Level of wealth inequality in countries that show up at least once on Forbes' list of billionaires.

Country	1987 (%)	1992 (%)	1996 (%)	2002 (%)
Argentina	–	1.3	2.5	1.0
Australia	1.0	0.7	0.4	1.4
Bahrain	–	–	16.4	–
Belgium	–	–	–	1.5
Brazil	2.0	1.5	2.4	2.9
Canada	3.3	2.9	2.6	6.2
Chile	–	7.2	11.5	4.3
China	–	–	–	0.1
Colombia	10.5	7.8	3.9	1.2
Denmark	–	1.0	2.6	2.4
Ecuador	–	–	5.6	–
France	0.4	1.3	2.3	4.5
Germany	2.2	4.9	5.4	10.5
Greece	–	3.8	9.8	2.3
Hong Kong	15.7	20.0	39.9	25.6
India	0.4	0.8	0.9	2.5
Indonesia	2.3	2.3	11.9	0.9
Ireland	–	–	–	1.1
Israel	–	–	1.9	5.6
Italy	0.9	1.0	1.3	3.2
Japan	3.5	2.2	1.9	1.5
Kuwait	4.8	–	9.5	14.9
Malaysia	–	4.3	25.4	10.0
Mexico	0.9	3.8	7.0	4.5
Netherlands	2.9	2.0	2.1	2.2
Norway	–	–	–	0.7
Peru	–	–	1.8	–
Philippines	–	2.3	28.2	6.9
Portugal	–	–	–	1.3
Republic of Korea	2.1	2.7	4.0	0.8
Russia	–	–	–	4.3
Saudi Arabia	8.2	10.6	12.0	24.6
Singapore	6.1	4.8	18.6	13.5
South Africa	–	–	2.9	4.0
Spain	0.4	0.7	0.7	2.5
Sweden	3.5	3.7	4.4	16.0
Switzerland	3.1	4.0	11.9	15.6
Taiwan	6.7	4.7	8.6	4.7
Thailand	–	3.7	11.6	1.8
Turkey	–	2.4	3.6	6.2
United Arab Emirates	–	–	–	2.4
United Kingdom	1.8	1.2	1.3	2.0
United States	3.2	3.7	5.7	8.3
Venezuela	–	1.7	3.4	10.1

The measure of inequality used is billionaire wealth, divided by GDP.

The following Table A3 notes the various standard errors that are obtained for wealth inequality when billionaire wealth is normalized by GDP in our base specification that includes income inequality, headcount poverty, and all other control variables.

The next two Tables A4 and A5 show how the standard errors change when billionaire wealth is normalized by physical capital stock and (separately) by population.

As the tables suggest, the standard error obtained by clustering in two dimensions is *smaller* than the standard error obtained by clustering along just the country dimension in two of the three cases. This result is not unusual and has been noted by (among others) Cameron and Miller (in press) who observe that: "if clustering has a modest effect, so cluster-robust and default standard are similar in expectation, then cluster-robust may be smaller due to noise." The pattern of standard errors that we observe also makes sense when we note that the standard errors obtained by clustering along the time dimension alone in Tables A3 and A4 are *smaller* than the OLS standard errors and the Huber–White standard errors which are robust to heteroskedasticity. Therefore, it is not surprising that the standard error on wealth inequality in these two tables by clustering along both dimensions is *smaller* than the standard error obtained by clustering just along the country dimension.[40] Thus to be conservative, throughout the paper, we have reported the standard error obtained by clustering just along the country dimension as it is generally the largest standard error we obtain with various alternative approaches to clustering (Table A5).

[40] As Thompson (2011) and Cameron, Gelbach, and Miller (2011) make clear, the relationship between the variance-covariance matrix where "i" and "t" are the two dimensions is: V(s.e. clustered by i & t) = V(s.e. clustered by i) + V(s.e. clustered by t) $- V_{\text{white}}$.

Table A2
Rank of countries with the lowest and highest level of politically connected wealth inequality on Transparency International's Corruption Perceptions Index for 1995 and 2012.

Sl. No.	Country	Rank of country in Transparency International's Corruption Perceptions Index	
		1995	2012
	Total number of countries on the list	41	174
1.	Hong Kong	17	14
1.	Netherlands	9	9
1.	Singapore	3	5
1.	Sweden	5	4
1.	Switzerland	8	6
1.	United Kingdom	11	17
	Median rank	9	8
	Mean rank	9	9
37.	Mexico	32	105
38.	Thailand	34	88
39.	Indonesia	41	118
40.	Colombia	31	94
41.	Malaysia	23	54
	Median rank	32	94
	Mean rank	32	92

The countries are ranked from lowest to the highest level of politically connected wealth inequality. The countries that are denoted with a 1. in the first column – Hong Kong, Netherlands, Singapore, Sweden, Switzerland, and United Kingdom appear in every year of the sample and have the lowest level of politically connected wealth inequality. Countries denoted with numbers 37. - 41. in the first column have the highest level of politically connected wealth inequality. Columns 3 and 4 are the ranks of each of countries on the Transparency International's Corruption Perceptions Index for the years 1995 (the first year when the index was constructed) and 2012 (the last year for which the data are available). The first set of median and mean ranks corresponds to the median and mean ranks of Hong Kong, Netherlands, Singapore, Sweden, Switzerland, and United Kingdom on the Corruption Perceptions Index. The last set of median and mean ranks correspond to the median and mean ranks of Mexico, Thailand, Indonesia, Colombia, and Malaysia.

Table A3
Standard errors obtained with "ivreg2" when billionaire wealth is normalized by GDP.

Assuming homoskedasticity	Robust to heteroskedasticity	Clustering by country	Clustering by year	Clustering along both dimensions
0.0439	0.0594	0.0737	0.0288	0.0523

Table A4
Standard errors obtained with "ivreg2" when billionaire wealth is normalized by capital.

Assuming homoskedasticity	Robust to heteroskedasticity	Clustering by country	Clustering by year	Clustering along both dimensions
0.2255	0.2691	0.3346	0.1143	0.2293

Table A5
Standard errors obtained with "ivreg2" when billionaire wealth is normalized by population.

Assuming homoskedasticity	Robust to heteroskedasticity	Clustering by country	Clustering by year	Clustering along both dimensions
12.750	11.846	12.691	12.749	13.538

Considering the small number of clusters along the time dimension, we also explored the use of the wild bootstrapping method proposed by Cameron et al., (2008). The use of such an estimation calls for specifying a null. Imposing a null hypothesis is practically done by estimating the model with the original sample, but leaving out the key regressor for which bootstrap test statistics are to be calculated. With that approach, we obtain a 95% confidence interval of [−0.1436, −0.03216] for wealth inequality, when billionaire wealth is normalized by GDP and the null for the country dummies are not specified. If the null for the country dummies is also provided along with the null on the other control variables, we obtain a 95% confidence interval of [−0.1324, 0.03422].

Therefore, on the basis of the results we obtain with "ivreg2" and "cgmwildboot", we feel confident that our conclusion with respect to the negative relationship between wealth inequality and economic growth is relatively robust to different approaches of clustering, including clustering in both dimensions.

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