Inequality and Growth: Industry-Level Evidence

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Abstract

Using a comprehensive data set of 22 industries in 86 countries over the period 1980–2012, we empirically identify the effect of inequality on industry-level value added growth. We show that an unequal income distribution increases the growth rates of physical-capital-intensive industries and reduces the growth rates of human-capital-intensive industries by lowering human capital and raising physical capital accumulation. These findings provide an explanation for the difficulties of the extant empirical literature to identify a clear-cut relationship between inequality and growth: the aggregate relationship between both variables depends on the relative importance of human and physical capital in a country's production structure.

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1 Introduction

Since the 1990s, a large body of empirical research has tried to establish the causal relationship between the distribution of income and economic growth. However, despite improvements in data quality and econometric techniques[1], the existing literature has not identified a uniform relation between both variables. Reduced-form estimates on a cross-country basis tend to estimate negative effects of inequality on growth (e.g, Alesina and Rodrik, 1994; Persson and Tabellini, 1994; Perotti, 1996), whereas specifications built on panel data suggest a positive relationship (e.g, Li and Zou, 1998; Forbes, 2000; Halter, Oechslin, and Zweimüller, 2014).

Even from a theoretical perspective, the net effect of inequality on growth is unclear. It is designed to be positive in classical models focusing on saving propensities and the accumulation of physical capital (Kaldor, 1957; Bourguignon, 1981), while models that build on credit market imperfections and the formation of human capital identify a negative relationship (Galor and Zeira, 1993).

The classical approach is based on the observation that savings rates are highest in upper income groups. As a consequence, income inequality channels resources towards individuals with higher savings propensities, which in turn increases economic growth through intensified investment activity. Hence, countries with higher degrees of income inequality should, ceteris paribus, perform better in terms of GDP growth than countries that exhibit lower degrees of inequality.

The credit market imperfection approach was pioneered by Galor and Zeira (1993) at a time when macroeconomic research renewed its interest in the determinants of economic growth (see Romer, 1986; Lucas, 1988; Barro, 1991). One potential determinant is the level of inequality, which is persistently negatively correlated with GDP across countries. That is, societies that are more equal are richer on average—a fact that can hardly be reconciled within a framework that proposes the savings rate channel as being the only link between inequality and income. Therefore, assuming indivisible investments in human capital and imperfect capital markets, Galor and Zeira (1993) show that the income distribution determines the allocation of human capital across individuals. In unequal societies, as a result, talented but poor individuals may be excluded from human capital augmenting investments—with potential adverse implications for aggregate output.

Taking both mechanisms together, inequality increases the supply of physical capital through higher savings and investments but decreases the supply of human capital through reductions in educational

[1] Deininger and Squire (1996) compiled a data set comprising only high-quality observations. This comprehensive and consistent panel laid the foundation for panel data investigations that are able to control for country-specific heterogeneity by applying the first-difference GMM estimator (e.g., Li and Zou, 1998; Forbes, 2000). As a further methodological improvement, Blundell and Bond (1998) constructed the system GMM-estimator. This estimator allows for the use of the level of inequality as an instrument, which increases the variation of the data. Critics, however, argue that the system GMM estimator suffers from a weak instrument problem when applied to the inequality-growth nexus (e.g, Bun and Windmeijer, 2010; Bazzi and Clemens, 2013). See Cingano (2014) for detailed explanations.

attainment. Therefore, the net effect of inequality is ambiguous, as a country's aggregate production function is typically increasing with respect to both input factors.

Unlike theoretical research (Galor and Moav, 2004), the empirical literature has not yet put forward a framework that takes these different effects of inequality on economic growth into account. This paper constitutes a first step into this direction. First, we expect the growth rates of physical-capital-intensive industries to be higher in countries with high initial levels of inequality. Second, higher inequality levels should reduce the long-run growth prospects of industries that are most dependent on high-skilled labor. To test these hypotheses, we compile a comprehensive data set that combines data on 22 manufacturing industries in 86 countries drawn from the UNIDO database for the 1980–2012 period with detailed country information on the degrees of inequality and industry information on the dependence on both human and physical capital. Applying disaggregated data on the industry-level enables us to focus on the effects of inequality on human and physical-capital-intensive industries separately. We thereby overcome the problem that the two effects offset each other, which could be the case in a framework based on aggregated data.

Our empirical tests start with a baseline model that establishes the effects of inequality on the growth rates of industries that vary in their ex-ante dependence on human and physical capital. Specifically, we model the average industry-level real growth rate of value added between 1980 and 2012 as a function of the interaction between a country's initial degree of inequality (measured by the GINI index) and an industry's dependence on human or physical capital, respectively, controlling for country and industry fixed effects. We find that higher income inequality raises the value added growth rates of physical-capital-intensive industries. The effect is significant and economically relevant: the annual value added growth differential between an industry at the 75th percentile of physical capital intensiveness (paper) and an industry at the 25th percentile (tobacco) is 0.8–1.1% higher in a country with a Gini coefficient at the 75th percentile (e.g., Turkey) than in a country at the 25th percentile (e.g., Israel) of the distribution of income. In contrast, human-capital-intensive industries grow significantly less in countries with a more unequal distribution of income. The annual value added growth differential between an industry at the 75th percentile of human capital intensiveness (instruments) and an industry at the 25th percentile (furniture) is 1.2–1.6% higher in a country with a Gini coefficient at the 25th percentile than in a country at the 75th percentile of the distribution of income.

These effects are non-trivial against the background of an average industry growth rate of 1.1% in our sample and they are robust to (i) using different inequality measures, (ii) employing alternative proxies for industry-level human and physical capital intensiveness, (iii) splitting the sample into various 10-year sub-samples and estimating panel data regressions, and (iv) changing the definition of the dependent variable.

We continue to examine the transmission mechanisms from inequality to the growth rates of physical and human-capital-intensive industries. Following the theoretical literature reviewed above, we focus on the role of two channels—the supply of human capital (proxied by the years of schooling) and physical capital (proxied by the real physical capital stock). To this end, we introduce interactions on the right-hand side of our regressions that capture these two channels. Particularly, we add the country-level stocks of human capital and physical capital interacted with the respective industry-level dependence on human and physical capital. Once we control for the country-level stock of human and physical capital, the coefficients on the inequality interactions lose their statistical significance. This result provides indirect evidence that the growth-related effects of inequality can be explained with theories based on human and physical capital accumulation. To complement this result with more direct evidence, we further document a negative (positive) relationship between the years of schooling (real physical capital stock) and inequality across the countries in our sample, which is also robust to including inequality with a significant lag (i.e., a 10-year and 20-year lag).

These results add to the existing literature in several dimensions. First, our results complement the existing empirical literature on the inequality-growth nexus (e.g., Persson and Tabellini, 1994; Perotti, 1996; Barro, 2000; Forbes, 2000; Easterly, 2007; Halter, Oechslin, and Zweimüller, 2014; Berg et al., 2018) by being the first—at least to the best of our knowledge—to track down empirically the effect of inequality on the economic performance of industries that differ in their ex-ante input factor dependencies. Second, we also contribute to the literature on the relationship between the distribution of income and investments in human capital (e.g., Galor and Zeira, 1993; Durlauf, 1996; Orazem and Tesfatsion, 1997). Finally, this paper conceptually contributes to the literature on the determinants of economic growth by applying cross-country cross-industry data, first proposed by Rajan and Zingales (1998). For its advantages, such as the rigorous way of dealing with endogeneity, this approach has been used extensively, especially on the relationship between finance and growth but also on the nexus between education and growth (e.g., Beck and Levine, 2002; Fisman and Love, 2003; Ciccone and Papaioannou, 2009; Brown, Martinsson, and Petersen, 2013).

The remainder of this paper is structured as follows. Section 2 introduces the data and empirical methodology. The main results are shown in Section 3. In Section 4, we identify the transmission channels from inequality to industry-level growth. The results of various robustness checks are presented in Section 5. Section 6 concludes the paper.

2 Data and Empirical Methodology

Empirical studies on the effects of inequality on economic growth are often subject to endogeneity concerns because (i) growth tends to affect the level of inequality (reverse causality) and (ii) unobserved heterogeneity can lead to omitted variable bias. These identification challenges are similar to those of the literature on the relationship between finance and growth. In this strand of the literature, the standard approach to overcome endogeneity is the cross-country cross-industry approach, pioneered by Rajan and Zingales (1998).

Consistent with this literature, we also achieve identification by using industry-level data, which allows us to treat inequality as broadly exogenous to growth on the industry-level because individual industries are too small to affect country-level measures of inequality. In addition, as industry data allow us to explore the within-country differences across sectors based on an interaction between a country and an industry characteristic, our estimates are less sensitive to potential omitted variables that may affect inequality levels, strengthening the causal interpretation of our coefficients. Particularly, even when other (unobserved) variables on the country-level correlate with the level of inequality, inter-industry differences in the sensitivity with respect to inequality should not be affected.[2]

A further advantage of this approach is that it allows the identification of particular channels between inequality and growth. This is important because the channels linking inequality with growth are potentially offsetting and, therefore, invisible to pure cross-country identification strategies. In particular, we focus on the human and physical capital channel of inequality by constructing industry benchmarks that capture each industry's reliance on both input factors. The following two sections give detailed explanations about data sources and the econometric specification applied.

2.1 Empirical Methodology

Our baseline test is based on the following regression equation:

$$\begin{aligned} \Delta\ ln\ y_{i,c,1980-2012} = \alpha\ ln\ y_{i,c,1980} + \lambda_i + \mu_c + \beta\ (GINI_{c,1980} * HCI_{i,1980}) \\ + \gamma\ (GINI_{c,1980} * PCI_{i,1980}) + \epsilon_{i,c}. \end{aligned} \tag{1}$$

The dependent variable ($\Delta\ ln\ y$) is the average growth rate in value added of industry i in country c over the 1980–2012 period. The main regressors of interest are the interactions between the 1980 Gini index ($GINI$), as our measure of income inequality, and a proxy for an industry's dependence on either human (HCI) or physical (PCI) capital, allowing us to identify the effects of inequality on the growth rates of industries with different input factor needs. Given the theoretical literature reviewed in the introduction, we expect the interaction coefficient related to physical capital (γ) to be positive, and the one related to human capital (β) to be negative. λ and μ are global industry-specific and country-specific fixed effects

[2] As argued by Ciccone and Papaioannou (2009), the cross-country cross-industry approach has also been proven useful in research areas where data availability is scarce and econometric inference is subject to multicollinearity concerns, which is often the case in cross-country growth regressions because countries that are similar in one dimension (e.g., GDP per capita) are often also similar with respect to other characteristics, such as financial development or the accumulated stock of human and physical capital (see also Table 1, Panel B).

that control for the heterogeneity across countries and industries. We further add the initial logarithm of value added as a control ($ln\ y$). $GINI$, HCI and PCI are subsumed in μ and λ and, therefore, do not enter the regression independently. $\epsilon_{i,c}$ is residual growth of industry i in country c. The standard errors are clustered at the country-level to account for the within-country correlation across industries.

2.2 Data

A. Country-Industry-Level Data

We draw data on value added from the 2015 version of the INDSTAT2 ISIC Revision 3 database of the United Nations Industrial Development Organization (UNIDO). It covers 22 manufacturing industries at the three-digit International Standard Industrial Classification (ISIC) for a large number of countries. We define the dependent variable as the average annual logarithmic growth rate of value added (deflated by the US producer price index) between 1980 and 2012. To ensure a high-quality sample, we drop the top and bottom 1% of value added growth rates so that our results are not driven by unrepresentative outliers. The US is dropped from our sample because it is used for industry benchmarking. Our most parsimonious specification then leaves us with a sample of 86 countries and 1,647 country-industry observations.

To capture the concept of growth convergence, we control for initial industry size. Whereas Ciccone and Papaioannou (2009) include the initial logarithm of value added of each industry-country observation, Rajan and Zingales (1998) add the initial share of an industry's value added in total country-level manufacturing value added. In our analysis, we follow the approach of Ciccone and Papaioannou (2009) because the number of industries providing data on value added in our sample varies significantly across countries. For instance, whereas the UK provides data for all manufacturing industries, Gambia only provides data on 14 industries. Consequently, employing the initial share of value added would potentially result in biased estimates, as the corresponding values for industries in Gambia are consistently higher than in the UK. Yet, as a robustness test, we document that our main results are robust to controlling for the initial share of value added, in line with Rajan and Zingales (1998).[3]

[3] In this test, we find that the statistical significance of the initial value added share is lower than the corresponding coefficient on the initial logarithm. Thus, in our sample, the initial logarithm of value added seems to be a better proxy for the concept of growth convergence than the initial share of value added.

B. Country-Level Data

We obtain our inequality data from the ALL THE GINIS data set compiled by Branco Milanovic (World Bank).[4] It combines data of various high-quality sources that use actual household surveys to calculate the Gini coefficients, such as the Luxembourg Income Study (LIS), POVCAL, or the World Institute for Development Research WIDER (WIIDI). One advantage of this data set is that it contains data on the income distribution for a wide range of countries, which maximizes the number of Gini coefficients in our sample without needing to rely on Gini estimates that have been produced by regressions or short-cut methods. For countries that do not report their Gini coefficient in 1980, we use the measurement of income inequality that is closest to 1980 (but we require it to be within a 15-year window around 1980).[5] Finally, in line with the existing literature, 6.6 points are added to each Gini coefficient that is expenditure/consumption-based (and that is, hence, not calculated using income data).[6] Table 10 (Appendix) reports the survey year of the Gini coefficient for each country.

Table 1 reports descriptive statistics of the Gini coefficient and its pairwise correlation with other country-level variables employed in various stages of the subsequent analysis. The logarithm of real per capita GDP and the logarithm of the real physical capital stock of machinery and non-transport equipment to GDP (PC) stem from the 9.0 version of the Penn World Table. Our measure of a country's human capital stock (HC) is the logarithm of the average years of schooling from the Barro-Lee data set. Financial development (FIN) is proxied by the ratio of private credit to GDP and is taken from the World Economic Indicators. All of these variables are measured in 1980.

The countries with the most equal income distribution in our sample are Hungary and Austria, while Malawi exhibits the highest degree of inequality. In general, as can be seen in Panel B of Table 1, countries with low levels of inequality tend to be richer, to have higher stocks of human capital and lower stocks of physical capital, and more sophisticated financial markets.

C. Industry-Level Data

Our measures of industry-level human and physical capital intensity are based on US data. The limited

[4] http://data.worldbank.org/data-catalog/all-the-ginis

[5] Many countries with high levels of inequality, such as Nicaragua and South Africa, do not report Gini coefficients prior to 1990. A shorter window around 1980 would, consequently, reduce the variation in our measure of inequality substantially. The inclusion of these observations to our data set is justified by the high persistence of Gini coefficients over time (see Christopoulos and McAdam, 2017).

[6] It is a usual correction (e.g., Halter et al., 2014) to account for the fact that expenditure/consumption-based Gini coefficients are systematically smaller than Gini coefficients calculated based on income data. 6.6 is the mean difference between Gini coefficients if both types of construction methods are available for the same country and year (Deininger and Squire, 1996).

Table 1: Descriptive Statistics and Correlations on the Country-level

Panel A: Descriptive Statistics

	Obs.	Mean	Min.	25^{th}	Med.	75^{th}	Max.
GINI	86	43.56	20.90	36.30	42.60	51.00	68.60
GDP	82	8.33	5.63	7.20	8.22	9.68	10.79
HC	81	1.61	-0.03	1.27	1.70	2.02	2.45
PC	80	3.33	1.52	2.64	3.07	3.98	6.26
FIN	79	34.53	2.19	18.16	29.54	46.50	127.87

Panel B: Correlations

	GINI	GDP	HC	PC	FIN
GINI	1.00				
GDP	-0.50	1.00			
HC	-0.51	0.76	1.00		
PC	0.34	-0.23	-0.27	1.00	
FIN	-0.41	0.59	0.43	-0.24	1.00

This table reports descriptive statistics of the Gini coefficient and pairwise correlations between the Gini coefficient with selected variables. Gini is taken from ALL THE GINIS data set. GDP is the natural logarithm of the real PPP-adjusted GDP per capita (in mil. US$) and PC refers to the logarithm of a country's physical capital stock of machinery and non-transport equipment over GDP (both in 1980). Both variables stem from the 9.0 Penn World Table. HC refers to a country's human capital stock and is measured by the logarithm of the average years of schooling in 1980, taken from the Barro-Lee data set. FIN is obtained from the World Economic Indicators data set and equals the ratio of private credit to GDP.

availability of industry data for a wider range of countries makes it necessary to rely on human and physical capital intensities from a benchmark country. In line with the extant empirical literature, we use US data as industry benchmarks because of both the detail and quality of US statistics and the degree to which US markets are relatively unaffected by financial and labor market frictions. Therefore, observed differences in human and physical capital dependencies across industries are likely to better reflect technological characteristics of industries.

The main identifying assumption underlying the choice of our US benchmarks is that the **rank order** of human and physical capital intensity across industries is the same in the US as in other countries of our data set. For instance, if chemicals require a higher human capital intensity than the tobacco industry in the US, they also require more human capital in Argentina. Thus, industries do not necessarily need to feature the same **level** of human and physical capital in different countries of our sample.

The data source of our human capital benchmark on the industry-level is the March supplement of the 1980 Current Population Survey. It contains individual-level data on each worker's years of schooling by four-digit industry classifications. This allows us to calculate the share of employees that have at least a high school degree (as our measure for human capital intensiveness (HCI)) at the UNIDO three-digit ISIC level. Table 2 reports the human capital intensiveness and descriptive statistics for all 22 industries. The most human-capital-intensive industries are petroleum, communication equipment, and chemicals, while the least human-capital-intensive sectors are textiles, apparel, and tobacco.

For our measure of physical capital intensiveness, we make use of the NBER manufacturing database (Bartelsman and Gray, 1996), which contains data at the six-digit industry classifications. Converting the database to the UNIDO three-digit ISIC, we calculate the amount of total real capital stock over value added as our measure of physical capital intensiveness (PCI). The most physical-capital-intensive industries are primary metals, stone, and petroleum, while the least physical-capital-intensive sectors are apparel, leather, and computing machinery.

Our industry benchmarks exhibit capital-skill complementarity indicated by a positive correlation between HCI and PCI. This correlation, however, is small enough (0.12) to avoid any problems associated with a low number of degrees of freedom. In particular, as human and physical capital intensiveness differ across industries, the various sectors can have heterogeneous reactions to inequality.

As a robustness test, we alternatively use European data to construct the industry-level human and physical capital intensities—to the best of our knowledge the only region reporting industry data on both physical and human capital dependencies (apart from the US). European data are also likely to provide a good industry benchmark because (i) the financial market frictions are arguably lower than in many other countries and (ii) a widespread public education system provides a relatively frictionless supply of human capital. Therefore, similar to the US, observed cross-industry differences in human and physical capital dependencies are likely to reflect technological characteristics of industries.

Specifically, we use the 1988 average industry-level employment shares of high-skilled workers in seven European countries (Belgium, Denmark, France, Germany, Netherlands, Spain, UK), as employed by Cörvers (1997).[7] Further, we calculate the 1995 real physical capital stock relative to value added for the different manufacturing sectors in the UK.[8] The resulting European human and physical capital benchmarks have a correlation with the corresponding benchmarks based on US data of 86% and 69%, respectively. These correlations suggest that inter-industry differences in human and physical capital intensity are indeed similar across countries, justifying the main identifying assumption of our analysis. In addition, as we show below, the baseline results are robust to these alternative industry-level input factor dependencies.

[7] The data are not available for 1980.

[8] The corresponding data for all of the seven European countries for which we have data on human capital intensity are not available. The data are also not available prior to 1995.

Table 2: Descriptive Statistics on the Industry-Level

	ISIC	HCI	PCI
Food	15	0.63	1.81
Tobacco	16	0.52	0.86
Textiles	17	0.51	1.95
Apparel	18	0.52	0.49
Leather	19	0.54	0.61
Lumber	20	0.55	2.08
Paper	21	0.74	2.23
Printing	22	0.61	1.00
Petroleum	23	0.86	2.42
Chemicals	24	0.81	2.31
Rubber and Plastics	25	0.69	2.14
Stone	26	0.64	2.63
Primary Metals	27	0.63	3.35
Fabricated Metals	28	0.68	1.36
Machinery	29	0.78	1.39
Computing Machinery	30	0.79	0.62
Electrical Equipment	31	0.78	1.04
Communication Equipment	32	0.81	1.01
Instruments	33	0.78	0.69
Automobiles	34	0.74	2.28
Other Transportation Equipment	35	0.74	0.81
Furniture	36	0.55	0.97
Mean		0.68	1.55
Standard Deviation		0.11	0.78
Median		0.68	1.38
75^{th} percentile		0.78	2.23
25^{th} percentile		0.55	0.86

This table reports descriptive statistics of our industry benchmarks, each comprising 22 different industries. HCI is the human capital intensiveness measured by the share of employees with at least high school education. PCI is the physical capital intensiveness measured by the total real capital stock per unit of value added.

3 Baseline Results

Table 3 presents our baseline results. Column (1) shows the results of a regression of industry growth on the Gini coefficient—without interacting it with the industry-level human and physical capital intensities. The corresponding coefficient is negative, but not statistically significant at conventional significance levels. We thus continue examining whether inequality has a significant impact on the growth rates of certain types of industries, conditional on their input factor dependencies.

To this end, we first interact the Gini coefficient with the industry dependency on human capital. Column (2) gauges that higher inequality is associated with lower growth rates of human-capital-intensive industries. This result is not only statistically but also economically significant: the annual value added growth differential between an industry at the 75th percentile of human capital intensiveness (instruments) and an industry at the 25th percentile (furniture) is 1.2% higher in a country with a Gini coefficient at the 25th percentile (e.g., Israel) than in a country at the 75th percentile (e.g., Turkey) of the distribution of income.[9]

Next, we interact inequality with the industry dependency on physical capital. As can be seen from column (3), a more unequal income distribution has positive effects on the growth of industries that are physical-capital-dependent. Again, this effect is also economically important: the annual value added growth differential between an industry at the 75th percentile of physical capital intensiveness (paper) and an industry at the 25th percentile (tobacco) is 0.8% higher in Turkey than in Israel.[10]

Finally, in the most saturated model specification (our benchmark specification), we include the interactions of GINI*HCI and GINI*PCI simultaneously. Column (4) indicates that a more unequal income distribution is still associated with lower growth of human-capital-intensive industries and higher growth of physical-capital-intensive industries. Both interaction terms are significant at the 5% level and the economic magnitude of the coefficients even rises relative to the previous specifications.

The result that both effects are similar in size but work into different directions rationalizes the insignificance of inequality in column (1): the net effect of inequality on economic growth is contingent on the relative importance of physical versus human capital in the economy. This possible source of ambiguity also helps to explain the lack of identification of a uniform relationship between inequality and economic growth in the extant literature that is based on aggregate data.

Apart from the specification of column (1), the coefficient on the initial level of value added is negative and

[9] The 75th percentile of the distribution of Gini indices is equal to 51 and the 25th percentile is equal to 36.3. The 25th percentile of the distribution of HCI is equal to 0.55; the 75th percentile is equal to 0.78. Using these values, we calculate the economic magnitude for the human capital channel as follows: $-0.366 * (0.78 - 0.55) * (36.3 - 51) \approx 1.2$.

[10] The 75th percentile of the distribution of Gini indices is equal to 51 and the 25th percentile is equal to 36.3. The 25th percentile of the distribution of PCI is equal to 0.86; the 75th percentile is equal to 2.23. Using these values, we calculate the economic magnitude for the physical capital channel as follows: $0.0401 * (2.23 - 0.86) * (51 - 36.3) \approx 0.8$.

statistically significant at the 1% level. This negative coefficient is in line with the literature on growth convergence (e.g., Baumol, 1986), indicating that large industries tend to grow less. Overall, the results of section 3 gauge the importance of income inequality in shaping industry-level dynamics. Consistent with the theoretical literature, we find that a more unequal distribution of income has both a negative impact on industries that rely on high-skilled labor and a positive effect on physical-capital-intensive sectors.

Table 3: Baseline Results

	(1) VA	(2) VA	(3) VA	(4) VA
GINI	-0.0261 (-0.54)			
GINI*HCI		-0.366* (-1.68)		-0.446** (-2.00)
GINI*PCI			0.0401* (1.98)	0.0536** (2.55)
INITIAL LEVEL	-0.336 (-1.59)	-0.888*** (-3.33)	-0.837*** (-3.12)	-0.903*** (-3.37)
Country FE	no	yes	yes	yes
Industry FE	yes	yes	yes	yes
N	1647	1613	1613	1613
adj. R^2	0.072	0.387	0.386	0.389

This table presents regression results on the effect of inequality on the performance of industries contingent on their human and physical capital intensiveness for the period 1980–2012. In particular, we regress industry-country-level value added growth (VA) on the interaction between the country-level Gini index and industry-level intensiveness of human capital (column (2)) and on the interaction between the country-level Gini index and the industry-level intensiveness of physical capital (column (3)). In column (4), we saturate our model by including both interaction terms simultaneously. All regressions include industry fixed effects (coefficients not reported) and the initial log of value added as additional regressors. Country fixed effects (coefficients not reported) are included in the models in columns (2)–(4). The model of column (1) does not control for country fixed effects. The t-statistics are based on standard errors clustered on the country-level and are reported in parentheses below the coefficients. * p<0.10, ** p<0.05, *** p<0.01.

4 Identifying the Transmission Channels of Inequality

We have established that inequality is associated with higher growth rates of physical-capital-intensive industries and lower growth rates of human-capital-intensive industries. We next present a battery of tests that explore the channels through which inequality affects the growth rates of these types of industries. Following the theoretical literature reviewed in the introduction, we focus on the role of two channels—the supply of human capital (proxied by the years of schooling) and physical capital (proxied by the real physical capital stock).

As shown by Galor and Zeira (1993), an unequal income distribution prevents talented but poor individuals from human capital investments, thereby, reducing the growth of human-capital-intensive industries. The small body of empirical research that has put this mechanism under scrutiny comprises Deininger and Squire (1998) who show that initial inequality in landholdings reduces both subsequent economic growth and the average years of schooling. Using data from the Panel Study of Income Dynamics, Mayer (2001) investigates how the increase in economic inequality between 1970 and 1990 has affected school attainment in the US. She finds that a one-standard deviation increase in income inequality (measured by the Gini coefficient) causes a 10% drop in high school graduation.

The theoretical literature further suggests that inequality increases the growth rates of industries that are dependent on physical capital because the propensity to save is an increasing function in income, raising aggregate savings and investments (Bourguignon, 1981). This finding is in line with the empirical evidence of Kuznets (1955), who refers to the fact that the richest 5% account for almost two-thirds of all savings in the US. In a more recent study, Dynan, Skinner, and Zeldes (2004) find a strong positive relationship between savings rates and both current and life time income that is robust to different concepts of savings rates.

In order to identify these channels as the relevant transmission mechanisms of inequality, we pursue a two-step approach. First, we follow an indirect approach by introducing interactions on the right-hand side of our regressions that capture the aforementioned channels through which inequality should affect industry-level growth. For the human capital channel, following Berg et al. (2018), we add the country-level years of schooling (in logs), interacted with industry-level human capital intensity. For the physical capital channel, we introduce the country-level real capital stock of machinery and non-transport equipment over GDP (in logs), interacted with the industry dependency on physical capital.[11] [12] To the extent that human and physical capital accumulation explain the growth-related effects of inequality, controlling for human and physical capital should reduce the statistical significance of inequality.

Second, we implement a direct regression approach, investigating the effect of inequality on the mechanism variables. Thus, for each of the two channel variables, we estimate a regression of the following form:[13]

$$Z_c = \eta \; GINI_c + \theta \; GDP_c + \epsilon_c \tag{2}$$

where θ is the effect of the 1980 logarithm of per capita GDP and η is the effect of the 1980 Gini coefficient on the respective mechanism variable (Z_c). In contrast to Equation 1, we are not able to add country fixed effects, as they would absorb the effect of per capita GDP and inequality. As an extension to this regression, however, we will also present a panel data version of Equation 2, allowing us to include different lags of the Gini coefficients and to control for country fixed effects.

The first three columns of Table 4 display the results for the indirect approach. As can be seen from column (1), saturating our regressions with the initial years of schooling (SCH), interacted with HCI, turns the original GINI*HCI interaction insignificant. This means that the link between inequality and the growth rates of industries dependent on human capital primarily works through differences in years of schooling. In line with earlier findings by Ciccone and Papaioannou (2009), the interaction between years of schooling and industry-level human capital intensity is positive and significant at the 5% level, indicating that industries that are most dependent on high-skilled labor grow faster in countries with higher educational levels. The interaction between the Gini coefficient and industries' physical capital intensity is unaffected by the inclusion of the additional interaction term. In column (2), we augment our baseline regression with the real capital stock in its interaction with PCI. Whereas GINI*HCI remains statistically significant at the 5% level, GINI*PCI loses its statistical significance, implying that inequality affects the growth of physical-capital-intensive industries mainly through the supply of physical capital. The previous results are also robust to the inclusion of years of schooling and the real physical

[11]We use the capital stock of machinery and non-transport equipment, rather than the total capital stock, as the latter includes residential real estate, which is arguably unrelated to the supply of physical capital in industries' production process and, hence, to physical capital driven growth. The data on the capital stock of machinery and non-transport equipment come from the capital details in the 9.0 version of the Penn World Table.

[12]All of the channel variables have a low time variation, which is important because Gini coefficients also display a pronounced autocorrelation. That is why inequality is highly correlated with the stock of human and physical capital, as shown below, but not, for instance, with the share of investments over GDP, a more volatile proxy for physical capital.

[13]We run these direct regressions on our country-industry level data set in order to be consistent with the previous indirect regressions. The results, however, are robust to implementing Equation 2 on a pure cross-country data set (without the industry dimension).

capital stock in their interactions with HCI and PCI simultaneously (column (3)). We thus provide evidence that the effect of inequality on industry growth is mainly transmitted through differences in the stock of human and physical capital.

Table 4: Identifying the Transmission Channels

	(1) VA	(2) VA	(3) VA	(4) HC	(5) PC
GINI				-0.00948**	0.0294***
				(-2.01)	(2.73)
GINI*HCI	-0.106	-0.512**	-0.111		
	(-0.42)	(-2.17)	(-0.42)		
GINI*PCI	0.0588***	0.0358	0.0382		
	(2.83)	(1.43)	(1.54)		
HC*HCI	11.58**		11.69*		
	(2.06)		(1.97)		
PC*PCI		0.646**	0.685**		
		(2.56)	(2.53)		
GDP				0.243***	-0.0763
				(6.31)	(-1.03)
INITIAL LEVEL	-1.164***	-0.951***	-1.131***		
	(-4.58)	(-3.47)	(-4.12)		
Country FE	yes	yes	yes	no	no
Industry FE	yes	yes	yes	no	no
N	1537	1496	1438	1453	1496
adj. R^2	0.395	0.397	0.399	0.596	0.133

In columns (1)–(3), the dependent variable is the annual growth rate of value added (VA) at the country-industry level for the 1980–2012 period. The main regressor is the country-level 1980 Gini index, interacted with industry-level human (HCI) and physical (PCI) capital intensity. All models include the initial log of value added at the country-industry level and country and industry fixed effects. In column (1), we also add the interaction of country-level years of schooling (in logs) and HCI. In column (2), we add the interaction of country-level real capital stock of machinery and non-transport equipment over GDP (in logs) and PCI. In column (3), we add both additional interaction terms simultaneously. In columns (4)–(5), we examine the effect of the Gini coefficient on the years of schooling (in logs) and the real capital stock of machinery and non-transport equipment (in logs), controlling for initial per capita GDP (in logs). The t-statistics are based on standard errors clustered on the country-level and are reported in parentheses below the coefficients. * p<0.10, ** p<0.05, *** p<0.01.

To corroborate this result, we continue presenting the results for the direct regressions of the mechanism variables on the Gini coefficient. The attendant results provide evidence in favor of the Galor-Zeira hypothesis: higher inequality in our sample is associated with lower human capital, i.e., less average years of schooling (column (4)). Column (4) also indicates that the years of schooling are higher in countries with higher per capita GDP. In column (5), we further identify a positive association between inequality and the real physical capital stock, consistent with the classical approach reviewed in section 1. The effects of inequality on the mechanism variables are not only statistically but also economically significant: a country at the 75th percentile of the distribution of Gini indices (Turkey), relative to a country at the 25th percentile (Israel), has a 13.9% lower human capital stock and a 43.2% higher physical capital stock.[14]

The previous evidence builds on a static empirical framework, regressing the mechanism variables (measured in 1980) on the Gini coefficient (measured in 1980). However, the relationship between inequality as well as the average years of schooling and the real physical capital stock might manifest with a significant lag. We thus continue presenting a panel data version of the preceding direct regressions, allowing us to include different lags (i.e., a 10-year lag and a 20-year lag) of the Gini coefficients on the right-hand side of Equation 2 and to control for country fixed effects. Due to these fixed effects, we identify the within-country effects over time of changes in inequality on changes in the mechanism variables. Apart from the specification of column (2), higher inequality is significantly associated with a reduction in the years of schooling and a higher physical capital stock. We thus uncover a robust impact of inequality on both mechanism variables. The sign of the coefficients is consistent with the recent literature (e.g., Mayer, 2001; Dynan, Skinner, and Zeldes, 2004; Berg et al., 2018).

In summary, Section 4 establishes that inequality is significantly associated with a higher physical capital stock and a lower human capital stock, consistent with the theories of the credit market imperfection approach and the classical approach. We also show that inequality affects industry-level growth mainly through differences in the stock of human and physical capital: once we control for the stock of human and physical capital, the effect of inequality on industry growth turns insignificant.

[14]The 75th percentile of the distribution of Gini indices is equal to 51 and the 25th percentile is equal to 36.3. As we take the logarithm of the dependent variable, we obtain the economic effect for HC as follows: $(51 - 36.3) * 100 * (-0.00948)$. Equivalently, the corresponding effect for PC is calculated as follows: $(51 - 36.3) * 100 * 0.0294$.

Table 5: Further Evidence on the Transmission Channels

	(1) HC	(2) PC	(3) HC	(4) PC
$GINI_{t-10}$	-0.00264***	0.00279		
	(-2.97)	(1.39)		
$GINI_{t-20}$			-0.00338***	0.00378*
			(-3.96)	(1.90)
GDP_{t-10}	0.301***	0.558***		
	(18.90)	(14.07)		
GDP_{t-20}			0.227***	0.493***
			(9.92)	(8.95)
Country FE	yes	yes	yes	yes
N	1097	1185	513	606
adj. R^2	0.954	0.912	0.978	0.950

In this table, we present a panel data version of the regressions of the mechanism variables on inequality. The dependent variables are the years of schooling (in logs), HC, and the real capital stock of machinery and non-transport equipment over GDP (in logs), PC. The main regressor is the lagged country-level Gini coefficient. All regressions also control for lagged per capita GDP (in logs) and country fixed effects. The t-statistics are based on standard errors clustered on the country-level and they are reported in parentheses below the coefficients. * p<0.10, ** p<0.05, *** p<0.01.

5 Robustness Checks

In this section, we present several robustness checks. In particular, we show that our results are robust to (i) using different inequality measures, (ii) employing alternative proxies for industry-level human and physical capital intensiveness, (iii) splitting the sample into various 10-year sub-samples and estimating panel data regressions and (iv) changing the definition of the dependent variable.

A. Are the Results Robust to Employing Income Shares of the Different Income Groups?

In our baseline specification, we employ the Gini coefficient as our measure of inequality because it is most widely used in the extant literature and has the highest data availability. However, the Gini coefficient only gives a partial picture of the slope of the income distribution and its potential effects on industry growth. For instance, an aggregate proxy for inequality does not allow for analyzing whether a low income share of the poorest or rather a low income share of the middle income class relative to the richest part of the population drives the growth-related effects of inequality identified in the baseline model. Therefore, we employ alternative variables for inequality in the following analysis: the income shares of five different income groups. Particularly, we replace the Gini coefficient with the income share of (i) the poorest 20% of the population, (ii) the poorest 20%–40%, (iii) the poorest 40%–60%, (iv) the poorest 60%–80% and (v) the richest 20%. Again, as in the previous specifications, we enable these variables to interact with an industry's dependence on human or physical capital.

To put these alternative measures of inequality into perspective, we report the summary statistics and the pairwise correlations between the Gini coefficients and the income shares of the five income groups in Table 6. As can be seen from Panel A, replacing the Gini coefficient with income shares comes at the cost of losing observations: the World Bank only reports data on income shares for 49 out of the 86 countries for which we have Gini coefficients in the baseline model. Panel B further reveals a high negative correlation between the Gini coefficient and income shares of all income groups—except the one related to the highest income. As a consequence, a high Gini coefficient is on average not only associated with a low income share of the poorest groups (First20, Second20), but also with a low income share of the middle- and upper-middle classes (Third20, Fourth20). The analysis undertaken in the baseline section was, thus, primarily based on cross-sectional differences in the income share of the top income group relative to the combined income share of the rest of the society. By respectively replacing the Gini coefficient with all five of the income shares, this section also makes use of cross-sectional differences across the income shares of the first four groups.

Table 7 shows that for the lowest four income groups, a higher income share (implying a lower average level of inequality) is associated with greater value added growth of human-capital-dependent industries. The size of this effect, however, varies across these groups, with the largest impact in the upper-middle income class: whereas the related coefficient in the fourth income group is equal to 4.5, it is only equal to 2.0–2.2 in the lowest two income groups.[15]

Turning to the physical capital channel, Table 7 indicates that lower inequality driven by higher income shares of the poorest two income groups reduces the growth rates of physical-capital-intensive industries, as can be gauged from the significant coefficients on the corresponding interaction terms in columns (1) and (2). As these income groups have a high marginal consumption rate, their additional income does not raise aggregate savings and investments and, as a consequence, the underlying channel behind the positive growth effects of inequality (see Section 4) cannot be at work. In contrast, increased inequality driven by higher income shares of the richest 20% (people with the highest propensity to save) leads to significantly higher value added growth rates of industries dependent on physical capital: the corresponding interaction in column (5) is positive and significant at the 10% level.

Overall, the previous test thus establishes that the link between inequality and industry-level performance is robust to alternative measures of inequality.

[15]The difference among the different income groups, however, should be interpreted with caution, as we are not performing a counterfactual analysis. Instead, we test whether countries in which inequality is driven by low income shares of the middle class, compared to countries in which inequality is driven by low income shares of the poorest part of the population, behave differently in terms of industry growth. The existing literature linking the income distribution to macroeconomic outcomes via their influence on human capital investments presents several explanations for a (possibly) weaker relationship between income shares of low income groups and educational investments. First, due to the presence of credit market imperfections, the poorest parts of society are distorted in their investments in human capital (e.g., Galor and Zeira, 1993). Given these credit market frictions, even a higher income share of the poorest part of the society does not raise educational investments. The second explanation departs from the assumption that children typically condition their expected returns to schooling on their parents' returns to schooling. Given this model setup, Orazem and Tesfatsion (1997) show that underinvestments in the education of low-income children might in part be due to disincentive problems caused by distortionary taxes that fund income transfers, but at the same time reduce the perceived returns to schooling, leading children to make inefficient use of their educational opportunities. A further explanation for the low correlation between income transfers to low-income groups and educational investments is presented by Durlauf (1996). In this paper, parents in different income groups vary in their abilities to optimally select a schooling environment for their children. Consequently, as children are passive recipients of the human capital investments of their parents, even lower liquidity constraints of poorer families do not raise their investments in human capital.

Table 6: Descriptive Statistics and Correlations between Different Measures of Inequality

Panel A: Descriptive Statistics

	Obs.	Mean	Std.	Min.	Max.
GINI	86	43.56	10.94	20.90	68.60
First20	49	5.18	2.39	0.84	11.42
Second20	49	9.32	2.73	4.34	15.39
Third20	49	13.86	2.45	9.31	18.51
Fourth20	49	20.88	1.68	17.32	23.65
Fifth20	49	50.76	8.76	32.37	64.98

Panel B: Correlations

	GINI	First20	Second20	Third20	Fourth20	Fifth20
GINI	1.00					
First20	-0.74	1.00				
Second20	-0.79	0.97	1.00			
Third20	-0.83	0.91	0.97	1.00		
Fourth20	-0.74	0.59	0.72	0.85	1.00	
Fifth20	0.82	-0.94	-0.99	-0.99	-0.82	1.00

This table presents descriptive statistics and pairwise correlations of the Gini coefficient and income shares of five different income groups. Gini is taken from ALL THE GINIS data set. The income shares of the five different income groups are taken from the World Development Indicators. First20 is the income share of the poorest 20% of the population, Second20 is the income share of the poorest 20%–40%, Third20 is the income share of the poorest 40%–60%, Fourth20 is the income share of the poorest 60%–80% and Fifth20 is the income share of the richest 20% of the population.

Table 7: Employing the Different Income Shares

	(1) VA	(2) VA	(3) VA	(4) VA	(5) VA
First*HCI	2.161*				
	(2.24)				
First20*PCI	-0.384**				
	(-2.94)				
Second20*HCI		2.061*			
		(2.45)			
Second20*PCI		-0.271*			
		(-2.34)			
Third20*HCI			2.641**		
			(2.90)		
Third20*PCI			-0.235		
			(-1.86)		
Fourth20*HCI				4.527***	
				(3.33)	
Fourth20*PCI				0.0197	
				(0.10)	
Fifth20*HCI					-0.726**
					(-2.85)
Fifth20*PCI					0.0731*
					(2.08)
INITIAL LEVEL	-0.748	-0.749	-0.758*	-0.765*	-0.758*
	(-1.95)	(-1.95)	(-1.98)	(-2.00)	(-1.98)
Country FE	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes
N	861	861	861	861	861
adj. R^2	0.382	0.381	0.381	0.382	0.381

The dependent variable in all models is the annual growth rate of value added (VA) at the country-industry level. In column (1), the main regressor is the interaction between the country-level income share of the poorest 20 percent of the population and industry-level human capital intensiveness (HCI) and physical capital intensiveness (PCI). In column (2), the main regressor is the interaction between the country-level income share of the second poorest 20 percent of the population and industry-level HCI and PCI. In column (3), the main regressor is the interaction between the country-level income share of the third poorest 20 percent of the population and both industry-level HCI and PCI. In column (4), the main regressor is the interaction between the country-level income share of the fourth poorest 20 percent of the population and both industry-level HCI and PCI. In column (5), the main regressor is the interaction between the country-level income share of the richest 20 percent of the population and both industry-level HCI and PCI. All specifications also include the initial log of value added at the country-industry level, as well as country fixed effects and industry fixed effects (coefficients not reported). The t-statistics are based on standard errors clustered on the country-level and are reported in parentheses below the coefficients. * p<0.10, ** p<0.05, *** p<0.01.

B. Are the Results Robust to Panel Regressions?

We continue to split our data into two 10-year (1980–1989 and 1990–1999) and one 13-year (2000–2012) period, which allows us to estimate panel data regressions. In particular, we regress the average 10 (13)-year value added growth rate of industry i in country j and at time period t on the initial country-level Gini index of the respective period (column (1)), and its interaction with HCI and PCI (columns (2)–(4)), controlling for the initial logarithm of value added, as well as industry-period and country-period fixed effects.[16] The advantage of this procedure is an increased statistical power and the possibility of controlling for a richer set of fixed effects.

Table 8 contains the attendant results. Consistent with our baseline results, column (1) suggests that inequality does not seem to have an aggregate effect on industry growth. We thus continue examining the interaction between inequality and the industry-level dependencies on human and physical capital. In columns (2)–(4), we find that higher inequality is associated with higher growth of physical-capital-dependent industries and lower growth of industries dependent on human capital. The corresponding magnitude of the estimates is similar to our baseline coefficients. Thus, the time variation introduced in this section does not increase the economic and/or statistical power of our analysis. This can, presumably, be attributed to the low time variation of Gini indices in most countries.

[16] As Gini indices in most countries exhibit low time variation, we are not able to include country-industry fixed effects. They would absorb most of the variation in GINI*PCI and GINI*HCI.

Table 8: Estimating Panel Data Regression

	(1) VA	(2) VA	(3) VA	(4) VA
GINI	-0.00712			
	(-0.12)			
GINI*HCI		-0.255*		-0.316**
		(-1.92)		(-2.27)
GINI*PCI			0.0336	0.0425*
			(1.59)	(1.94)
INITIAL LEVEL	-0.512**	-1.086***	-1.080***	-1.102***
	(-2.62)	(-3.89)	(-3.83)	(-3.92)
Country-Period FE	no	yes	yes	yes
Industry-Period FE	yes	yes	yes	yes
N	4129	4056	4056	4056
adj. R^2	0.066	0.401	0.400	0.401

In this robustness test, we split our data into two 10-year (1980–1989 and 1990–1999) periods and one 13-year (2000-2012) period and estimate panel data regressions. In particular, we regress the average 10 (13)-year value added growth rate of industry i in country j and at time period t (VA) on the initial country-level Gini index of the respective period, interacted with the industry-level intensiveness of human and physical capital. All models include the initial log of value added and industry-period and country-period fixed effects (apart from column (1) which is without the latter). The t-statistics are based on standard errors clustered on the country-level and are reported in parentheses below the coefficients. * p<0.10, ** p<0.05, *** p<0.01.

C. Additional Robustness Tests

In this section, we perform various additional robustness tests, which are based on the baseline specification of Equation 1, but adjust the econometric model in one particular dimension each. Specifically, we employ alternative measures of industry-level human and physical capital intensity, industry growth and inequality, include an additional control on the right-hand side of Equation 1 and alter the country and time coverage of our sample. These adjustments are presented in Table 9.

In our baseline specifications, we use US data as industry benchmarks for physical and human capital intensity because of both the detail and quality of US statistics and the degree to which US markets are relatively unaffected by financial and labor market frictions.[17] Alternatively, we now use European data to construct the industry-level human and physical capital intensities. European data are also likely to provide good industry benchmarks because (i) the financial market frictions are arguably lower than in many other countries and (ii) a widespread public education system provides a relatively frictionless supply of human capital. Therefore, similar to the US, observed cross-industry differences in human and physical capital dependencies are likely to reflect technological industry characteristics. As can be seen

[17] A further reason for using US data is that the data are unavailable for most countries in our sample.

from column (1), we still find that inequality is associated with lower growth of human-capital-intensive industries and higher growth of physical-capital-dependent industries. The corresponding interaction coefficients are statistically significant at the 5% (for the HCI interaction) and 10% level (for the PCI interaction). Therefore, our results are unaffected by the choice of human and physical capital benchmarks.

In order to show that our baseline results are robust to employing Gini coefficients from other data sets, we next use the Gini indices of disposable income from the SWIID database. It consists of standardized inequality indicators from various data sets, which increases the coverage and usefulness of available income inequality data for broad cross-national research. The pairwise correlation between Gini indices from the SWIID database and the previously employed ones from the ALL THE GINIS database is equal to 92%. Thus, we do not expect to obtain significantly different results once we make use of the SWIID data. As can be seen from column (2), our baseline results are indeed largely unaffected when using Gini coefficients from the SWIID data set. In particular, the interaction of GINI*PCI remains positively significant and the interaction of GINI*HCI remains negatively significant at the 1% and 10% level, respectively.

In our baseline analysis, following Ciccone and Papaioannou (2009), we controlled for the initial 1980 logarithm of industry-country-level value added in order to capture the concept of growth convergence. Alternatively, we now control for the initial share of an industry's value added in total country-level manufacturing value added in 1980, the approach followed by Rajan and Zingales (1998). As can be seen from column (3) of Table 9, our main results on the interaction between Gini coefficients and HCI or PCI, respectively, are robust to controlling for the share of value added instead of its initial logarithm. Consistent with our previous results, we also find the initial share of value added to be negative, corroborating the result that larger industries tend to grow less. Yet, the statistical significance of the initial value added share is lower than the corresponding coefficient on the initial logarithm. Thus, in our sample, the initial logarithm of value added seems to be more appropriate in capturing the concept of growth convergence.[18]

We continue using an alternative dependent variable—the industry-country level growth in employment, instead of growth in value added. Accordingly, we also control for the logarithm of the initial employment level (INITIAL EM). Column (4) indicates that, again, we identify a positive link between inequality and physical capital driven growth and a negative link between inequality and human capital driven growth. Therefore, the effect of inequality on industry growth does not only manifest in differential value added growth rates but also in different employment growth rates across industries conditional on their input

[18]As argued in Section 2, this is likely to be the case because the number of industries providing data on value added varies significantly across countries. For instance, whereas the UK provides data for all manufacturing industries, Gambia only provides data on 14 industries. Consequently, the initial share of value added for each industry in Gambia is consistently higher than in the UK, thereby potentially biasing the results.

factor dependencies.

Next, we also control for the original Rajan-Zingales term—the interaction between the country-level size of the domestic financial system, proxied by the ratio of domestic credit provided by the financial sector relative to GDP, and industry-level external financing needs. Column (5) documents that our baseline results are also robust to adding the original Rajan-Zingales term to our model. Consistent with Rajan and Zingales (1998), we find the interaction between financial depth and industries' external finance needs to be positive, indicating that industries with a high dependence on external finance grow more in countries with larger financial sectors. Yet, the coefficient has a statistical significance just below the 10% level.

So far, we have established a link between industry growth and the **initial** levels of inequality. Generally, GINI coefficients are highly correlated over time. In several countries in our sample, however, they change significantly during the sample period of 1980-2012, thus potentially affecting the relationship between industry-level growth and the **initial** levels of inequality. The following robustness test examines whether our baseline results are robust to excluding these countries from the sample. Particularly, we omit countries from the following analysis in which GINI coefficients have changed by at least five percentage points during the sample period. Column (6) of Table 9 confirms that our estimates are unchanged. Inequality still increases physical capital driven growth and reduces human capital driven growth, as can be gauged from the t-statistics of 2.05 and -2.08 on the respective interaction terms.

As the final robustness check, we restrict our analysis to the period of 1980–1999. This exercise is important in order to circumvent possible cross-industry disruptions associated with the early 2000s recessions and the great recession of 2007–2009. These results, presented in column (7) of Table 9, gauge that the coefficients on the inequality interactions are not statistically different from those in our baseline analysis: inequality still has positive effects for physical capital driven growth and negative effects for human capital driven growth.

Table 9: Additional Robustness Checks

	(1) VA	(2) VA	(3) VA	(4) EM	(5) VA	(6) VA	(7) VA (80-99)
GINI*HCI			-0.367	-0.542***	-0.435*	-0.574**	-0.493*
			(-1.66)	(-3.29)	(-1.74)	(-2.08)	(-1.67)
GINI*PCI			0.0520**	0.0384**	0.0503**	0.0497**	0.121***
			(2.41)	(2.08)	(2.28)	(2.05)	(3.33)
GINI*HCI(EUR)	-1.415**						
	(-2.45)						
GINI*PCI(EUR)	0.0189*						
	(1.80)						
SWIID*HCI		-0.335*					
		(-1.71)					
SWIID*PCI		0.0546***					
		(2.98)					
FIN*RZ					0.0584		
					(1.52)		
INITIAL LEVEL	-0.625*	-0.823***			-0.956***	-1.020**	-1.225***
	(-1.67)	(-3.26)			(-3.43)	(-2.00)	(-3.07)
INITIAL SHARE			-6.843**				
			(-2.22)				
INITIAL EM				-1.799***			
				(-6.61)			
Country FE	yes	yes	yes	yes	yes	yes	yes
Industry FE	yes	yes	yes	yes	yes	yes	yes
N	916	1591	1613	1622	1471	1367	1613
adj. R^2	0.366	0.390	0.380	0.294	0.393	0.277	0.326

This robustness table is based on the full baseline specification of Table 3, column (4), but with each column containing one adjustment. Column (1) employs industry-level human and physical capital intensities that are based on European data. In column (2), we employ Gini coefficients from the SWIID database. Column (3) controls for the industry-country-level value added share, instead of the initial logarithm of value added. In column (4), we use industry-country-level employment growth (EM) as the dependent variable and, accordingly, control for the initial log of employment. In the specification of the model presented in column (5) the Rajan-Zingales term (industry-level finance dependency and country-level financial development) is added to the baseline specification. In column (6), we restrict the data set to countries in which Gini coefficients have changed by less than 5 percentage points over the 1980–2012 period. Column (7) shows results of a model where the value added growth rates are calculated over a shorter time period (1980–1999). All specifications also include country and industry fixed effects (coefficients not reported). The t-statistics are based on standard errors clustered on the country-level and are reported in parentheses below the coefficients. * p<0.10, ** p<0.05, *** p<0.01.

6 Conclusion

Whereas theoretical models that focus on credit market imperfections and the formation of human capital find that inequality has negative implications for economic growth, theories that build on saving propensities and the accumulation of physical capital establish a positive relationship between both variables. However, unlike the theoretical literature, empirical research has not yet proposed a framework that takes this ambiguity about the effects of inequality on economic growth into account. In this paper, we aim to fill this gap by compiling a comprehensive industry-level data set that covers 22 industries in 86 countries over the 1980–2012 period to empirically identify the transmission mechanisms of inequality. We find that higher income inequality increases the growth rates of industries that are dependent on physical capital. In contrast, human-capital-intensive industries grow less in countries with a more unequal distribution of income. We further identify the transmission channels from inequality to industry-level growth. In particular, we gauge that a lower human capital stock (less years of schooling) associated with a more unequal income distribution drives the negative growth effects of inequality. Additionally, we find higher inequality levels to have positive effects on industry growth through a higher physical capital stock.

We finish by noting that our empirical strategy does not allow for determining the aggregate effect of income inequality on economic growth. However, this paper suggests that policy makers should keep in mind the potential negative implications of inequality in case their country's industrial structure relies largely on human capital.

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Appendix

Table 10: Gini Coefficients and Survey Year

Country	GINI	GINI YEAR
ARG	39.29	1980
AUS	39.29	1979
AUT	23.00	1987
BDI	39.89	1992
BEL	28.29	1979
BFA	53.09	1994
BGD	39.00	1981
BGR	25.00	1980
BHS	43.09	1979
BOL	52.69	1989
BRA	57.79	1980
BRB	48.90	1979
CAF	67.90	1992
CAN	35.79	1980
CHL	53.20	1980
CHN	32.00	1980
CIV	47.79	1985
CMR	55.59	1983
COL	54.70	1978
CRI	45.00	1979
CYP	30.50	1990
DEU	36.59	1980
DNK	41.29	1980
DOM	45.00	1976
DZA	38.79	1988
ECU	50.50	1987
EGY	43.59	1975
ESP	34.50	1980
FIN	30.89	1980
FJI	43.00	1977
FRA	31.10	1979
GAB	63.20	1977
GBR	28.70	1980
GHA	42.00	1987
GMB	46.29	1992
GRC	39.89	1981
GTM	47.29	1979
HKG	37.29	1980
HND	57.09	1989
HUN	20.89	1982
IDN	42.19	1980
IND	41.69	1978
IRL	36.00	1980
IRN	51.69	1984
ISR	36.29	1979
ITA	33.20	1980
JAM	51.09	1975
JOR	47.39	1980
JPN	33.40	1980
KEN	57.29	1981
KOR	38.59	1980

Country	GINI	GINI YEAR
LKA	42.00	1980
LSO	67.59	1986
MAR	45.79	1985
MDG	52.39	1980
MUS	45.70	1980
MWI	68.59	1993
MYS	51.00	1979
NGA	35.20	1981
NIC	56.29	1993
NLD	28.10	1979
NOR	26.79	1979
NZL	34.79	1980
PAK	38.89	1979
PAN	47.50	1980
PER	58.00	1981
PHL	45.20	1975
PNG	39.19	1995
POL	24.89	1980
PRI	50.2	1979
PRT	36.79	1980
PRY	38.90	1990
ROU	21.79	1989
SEN	52.70	1991
SGP	40.70	1980
SLV	48.40	1977
SWE	32.40	1980
SWZ	67.30	1995
TTO	41.70	1981
TUN	49.59	1980
TUR	51.00	1973
TZA	50.59	1977
URY	43.70	1981
VEN	39.40	1979
ZAF	63.00	1990
ZMB	51.00	1976

This table presents the Gini coefficients for all countries included in our baseline model. The countries are ordered by their world bank code. GINI is taken from ALL THE GINIS data set. GINI YEAR is a variable capturing the year in which the income distribution survey was conducted in each country.