Income Inequality and Technological Adoption*

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Abstract

We relate technological adoption (of different technologies) with income inequality. We discovered that some technologies such as aviation, cell phones, electric production, internet, telephone, and TV are skill-complementary in raising inequality. We constructed standardized indexes of skill-complementary technological adoption for modern Information and Communication Technologies (ICT), older ICT, production and transport technologies. We found strong evidence that older ICT and transport technologies (and less frequently modern ICT) tend to increase inequality. Additionally, we discovered that results are much stronger in rich countries than in poor ones. Our results are quite robust to a series of changes in specifications, estimators, samples, and measurement of technology adoption. These results may bring insights to the design of incentive-schemes for technology adoption.

Keywords: income inequality, technological adoption.
JEL Codes: I32, O10, O33, O50.

1 Introduction

A strong and active theoretical literature seeks to explain the rise of income inequality in the second-half of the twentieth century alongside the rise in the supply of human capital. Skill-biased technical change and capital-skill complementarity are crucial to explain these

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phenomena. Generally, according to theory, skill-premia increase due to two effects. First, the skill premium would reflect the productivity difference between sectors. Second, with full capital mobility, factor price equalization requires capital to flow to the sector operating with the new technology. There is some literature that evaluate empirically the skill-biased mechanism in different contexts, and a large majority confirms it, as will be evident from the following revision of the literature. Notwithstanding, whatever the explanation may be for the rise in income inequality and its relationship with technology, there is very little quantitative literature on the issue, as observed by (Hornstein et al., 2005, page 1361). In particular, empirical studies that test the skill-biased channel in determining cross-country inequality levels are scarce. Our aim is that this paper contributes to fill this gap.

This paper's contribution is threefold: first, it uses a large dataset on technology adoption (from Comin and Hobijn (2009)) to evaluate their effect on income inequality; second, it contributes to empirically test the skill-biased technical biased theory as it uses a measure of the complementarity between skills and technologies; third, it evaluates the effects of different technologies on inequality taking into account country heterogeneity, cross-country dependence and endogeneity to common factors.

We are thus able to identify which technologies are most equality-friendly or inequality-friendly and with this we highlight some new evidence. In particular, we are able to evaluate for the first time the effect of the adoption of some individual technologies (such as tractors, TV, aviation, railways, etc.) whose effect has been neglected in the study of inequality. To this end, we have also obtained measures of aggregate technology adoption by type of technology - modern ICT, older ICT, production, and transport technologies. Our main conclusions point to a positive effect of older ICT technologies (includes radios, mainline telephone lines, televisions in use, and telegrams) and transport technologies (includes aviation, railways lines, steamships, passenger cars, and commercial vehicles), and to a lesser extent of modern ICT technologies (includes computers, ATMs, internet users, and cell phones). Our results also indicate that the effects of technology adoption may be quite different from country to country and from groups of rich and poor countries.

The remainder of the paper is organized as follows. In Section 2, we discuss the related literature on the relationship between innovation and inequality. In Section 3 we describe our data set and respective sources. In Section 4 we describe our estimation strategy. In Section 5 we describe our results using estimators robust to country heterogeneity, cross-dependence, and endogeneity. Section 6 concludes.

2 Literature Review

A widely documented fact for the United States is that both the supply and wages of skilled labor relative to those of unskilled labor have grown markedly over the postwar period. (see e.g. Bound and Johnson (1992), Goldin and Katz (2010), or Acemoglu and Autor (2011). The literature has tended to explain this growing wage inequality by skill-biased technical change (SBTC). This is defined as a change in the production technology that favors skilled over unskilled labor by increasing its relative productivity and, hence, relative demand. Workers in the new technologies sectors are thus endowed with more capital, which raises their relative wages (Acemoglu (2002a), Acemoglu (2002b), Acemoglu (2003)).

An alternative development has argued that the diffusion of IT - General Purpose Technologies - may have increased the demand for adaptable skilled workers and made vintages of capital more adaptable. This in turn increases the premium of workers that show a lower learning cost and that can adapt quickly from one sector to another. These ideas have been formalized by Galor and Tsiddon (1997), Greenwood and Yorukoglu (1997), Caselli (1999), Galor and Moav (2000), and Aghion et al. (2002).

However, the relationship between innovation, employment and wage inequality has not been consensual. For example, Bogliacino and Lucchese (2016) uses the example of Germany unification controlled by other similar groups of countries and concluded that wage inequality varies essentially due to labor market arguments, rejecting the skill-biased channel. Also, Goos et al. (2014) documents that job polarization cannot be described by the skill-based technical change theory. The author develop a framework to explain job polarization using routine-biased technological change and offshoring. This model can explain much of both total job polarization and the split into within-industry and between-industry components for which offshoring is an essential explanation. However, offshoring is itself explained by technological progress. Los and Vries (2014) derive a new measure of technological change in vertically integrated production chains and show that it has been skill-biased. They find that skill-biased technological change has played the most important role in the different employment growth rates of high-skilled, medium-skilled and low-skilled labour in advanced countries. For emerging countries, the patterns of employment growth are very heterogeneous. For example, Gallego (2012), using data for Chile from 1960 to 2000, present sectoral and macro evidence according to which the relative demand for skilled workers is a consequence of international transmission of skill upgrading technologies from developed countries. Meschi et al. (2011) present similar results using a wide sample of firms in Turkey. Contrasting to these results are those from Pavcnik (2003) who for Chile in the years 1980s discover that plant adoption of foreign technology is not associated with plant skill upgrading. On the effect of openness on wage inequality, Meschi and Vivarelli (2009) showed that trade with high income countries worsen income distribution in developing countries, through both imports and exports. These findings provide support to the hypothesis that technological differentials and the skill biased nature of new technologies may be important factors in shaping the distributive effects of trade. Yeaple (2005) devised a model in which openness can induce firms to switch technologies, increase trade volumes, and the wage premium paid to the most highly skilled workers and a decrease in the wage premium paid to moderately skilled workers. Thus empirical literature has not been completely consensual on the validity of the skill biased nature of innovation or adoption of new technologies.

There is also a parallel literature focusing on the effects of technological progress on the employment/unemployment levels and thus indirectly on the skill premium. On the side of the positive effects of innovation on employment, we could find Ciriaci et al. (2016). This paper's evidence suggests that being innovative supports and stabilises a firm's organic employment growth pattern and being smaller and younger seems to be a sufficient condition to experience high employment growth. On the side of negative effects of innovation on employment, we found Frey and Osborne (2013), studying the effect of computarisation on employment. According to their estimates, about 47 percent of total US employment is at risk with computarisation. Also, they show evidence according to which wages decrease with computarisation. As computarisation mostly affects low-skilled jobs, this would tend to increase inequality between skilled and non-skilled workers. As the authors point out, technologies such as computers are complements to high-skilled workers and substitutes to low-skilled workers. Vivarelli (2014) argues that process innovation tend to be labor saving and product innovation labor friendly thus pointing out to a mix result of innovations on employment. On the same line, Marcolin et al. (2016) addresses the role of global value chains (GVCs), workforce skills, ICT, innovation and industry structure in explaining employment levels of routine and non-routine occupations. The analysis encompasses 28 OECD countries over the period 2000-2011 and the results point to the existence of complex interactions between the routine content of occupations, skills, technology, industry structure and trade, which do not allow for a neat identification of winners and losers in a GVC context. While the effects appear heterogeneous across quartiles of routine intensity, a persistent and positive role of skills and innovative output for employment is found across all quartiles of routine intensive occupations.

On the other hand, some literature has dedicated to the effects of employment on technological progress, an issue that our paper does not address. For example, in Grimalda (2016) the contrasting effects of labour market rigidity on efficiency are investigated in a model where there is non-general purpose technological change and different types of skills are available to workers. The trade-off between these two mechanisms results in an inverse-U shaped relationship between output and labour market rigidity, which implies that a positive level of labour market rigidity is in general good for the economy.

In the vision of Gordon (2012), the frontier economies economic growth is falling down in face of several headwinds that are in the process of dragging long-term growth, such as demography, education, inequality, globalization, energy/environment, and the overhang of consumer and government debt. According to the author, the innovations driven by the third industrial revolution had an effect in productivity that faded away more quickly than the one provoked by the innovations of the previous industrial revolutions. In fact, these innovations, such as computers and internet, IPADs and IPODs (Information and Communication Technologies - ICTs) were enthusiastically adopted, but they provided new opportunities for consumption on the job and in leisure hours rather than a continuation of the historical tradition of replacing human labor with machines. Brynjolfsson and McAfee (2014) present a much more positive view about the role of the ICTs in the world of innovations. They advocate that ICT may be considered a General Purpose Technology, such as the steam engine or the electric power. While Gordon (2012) puts them in contrast, Brynjolfsson and McAfee (2014) consider them in the same line, and argue that they will be the base of a future changing world. In this paper we also contribute to this conflicting opinions about the effect information, communication and digital technologies have on the economic outcomes, focusing on income inequality.

In fact, empirical attempts to evaluate the relationship between technological adoption and inequality are mostly country-specific as are Ding et al. (2011) and Rattso and Stokke (2013), for example. Barro (2000) and Jaumotte et al. (2013) examined this relationship in large samples of countries. Barro (2000) presents fixed-effects estimations of equations of the Gini index on covariates such as GDP and GDP squared, schooling, democracy index, openness, rule of law index, and several dummies. In his fixed-effects estimations, dummies for income or spending, secondary and higher education are negatively related to inequality and openness is positively related to inequality. Primary schooling and the dummy for individual or household data are insignificantly related to the Gini coefficient. There is a strong inverted-U relationship with GDP: the so-called Kuznets curve. Recently, Jaumotte et al. (2013) have re-assessed the determinants of inequality. They focused on the effect of globalization on inequality but do not go into the relationship between inequality and GDP. They concluded that trade globalization decreases inequality while financial globalization increases inequality. Moreover, information and communication technologies and credit deepening increases inequality while the share of industry in the economy decreases it. Education variables and initial GDP (when included) are insignificantly related to inequality. The evidence relating different types of technologies and inequality, as far as we know, does not exist. We contribute to fill this gap.

In the next Sections, we will see that the modern information and communications technologies (on the contrary to what happened with older ICT) are currently having small effects on wage inequality.

3 Data and Sources

There are currently three different projects that collect and make publicly available inequality data for many countries and periods around the world: the Luxembourg Income Study (LIS), the data set assembled by Deininger and Squire (1996) for the World Bank (WIID), recently updated and upgraded by the WIDER (World Institute for Development Economic Analysis) project, and the most recent standardized World Income Inequality data set (SWIID), by Solt (2009). The LIS, which was used by Jaumotte et al. (2013), has generated the most-comparable income inequality statistics currently available but covers relatively few countries and years. The Deininger and Squire data set and its successors, used by Barro (2000), on the other hand, can be used to provide many more observations, but only at a substantial loss of comparability. Solt (2009) implemented a sequence of steps to standardize income inequality data and provide data with wider coverage than the WIID, but at the highest quality as in LIS. However, in the process of standardization, not all countries had the sufficient data in the original sources. To handle this, Solt (2009) also calculated a standard-error of each Gini coefficient to account for the remaining uncertainty in data. We use data for inequality from the Standardized World Income Inequality database (SWIID), version 4.0, from Solt (2009), for the Gini coefficient and for the respective standard-error.[1] This includes data on the Gini coefficient, using post-taxes, post-transfers income (the net definition) and on the Gini coefficient, using pre-taxes, pre-transfers income (the market definition), and the respective standard-errors by country and year. We selected the net definition of the Gini coefficient as it accounts for the distortionary effects that fiscal systems have on income distribution of countries. Our measure of uncertainty-corrected Gini index is the following:

$$Gini_{i,t} = \frac{GINI_{i,t}}{1 + sd(GINI)_{i,t}} \tag{1}$$

where $Gini_{i,t}$ is the net definition of the Gini index given by the 4.0 version of the SWIID and $sd(GINI)_{i,t}$ is the standard-deviation of the net definition of the Gini index given by the 4.0 version of the SWIID, which measures the uncertainty or measurement error of the Gini index.

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

For technologies adoption we use the CHAT database from Comin and Hobijn (2009) and concentrate on the 20 largest technologies as used in Comin et al. (2013). First, we will present results on the effect of individual technologies on inequality. For each measure, and inspired in the theory that relates skill-technological complementarities with inequality Acemoglu (1998), we consider a measure of skill-technological complementarity for each pair country (i), year (t), such as:

$$Techh_{j,i,t} = tech_{j,i,t} \times hc_{i,t} \tag{2}$$

where $Techh_{j,i,t}$ is our measure of technology (considering skill-technological complementarity, $tech_{j,i,t}$ is the natural logarithm of one of the j technology adoption measures coming from Comin and Hobijn (2009), and $hc_{i,t}$ is the natural logarithm of the human capital measure coming from the Penn World Tables 8.0. We also use as an additional control variable, which may influence inequality, the log of the Openness ratio from the Penn World Tables 8.0. Education variables and openness variables are also in the earlier articles that studied the determinants of inequality in a large cross-section of countries Barro (2000) and Jaumotte et al. (2013) and so, we will also include them in our regressions.

Below, in order to summarize information about technologies adoption, we create additional variables such as ICT(modern), Transportation, Production and ICT (older). Each of these are sums of standardized values of technologies $Techh_{j,i,t}$ that lie in each category. In the modern ICT we included computers, ATMs, internet users, and cell phones. In the Transportation we included civil aviation passenger-kilometers traveled, civil aviation ton-kilometers traveled, public railway lines, passenger journeys by railway in passenger-kilometer, freight carried on railways (excluding livestock and passenger baggage), steamships, passenger cars and commercial vehicles. In the Production technologies we include wheel and crawler tractors, (excluding garden tractors), gross output of electric energy (inclusive of electricity consumed in power stations) in Kw-Hr, crude steel production (in metric tons) in blast oxygen furnaces and crude steel production (in metric tons) in electric arc furnaces. For the older ICT we included number of radios, mainline telephone lines, number of televisions in use and telegram. For each of the constructed technologies types, and in order to maximize the time-series coverage, we considered that each sum includes values when at least one of its components has values in each country-year pair. Any missing value is also taken as evidence of no technology adoption. We will also discuss results with alternative assumptions that, of course, come at the cost of lower coverage.[2]

We end up with an unbalanced panel database of a maximum of 111 countries with a minimum of 1 year *per* country and a maximum of 42 years *per* country. The initial year covered is 1960 and the last 2003. These values depend on the technology considered. Among the technologies with excellent coverage in the database, we count electrical production, tractors, rail line, telephone, TV, and vehicles. On the contrary ATMs, internet, ships and steel are among the less covered. Coverage oscillates between 368 observations (ATMs) to 5991 observations (electrical production). Table 1 shows descriptive statistics for all the variables included in the analysis. Details for definitions and sources are given in the Appendix.

[2]Had we restricted the technology-types measures to sums in which all the parcels had non-missing values, the resulting number of observations would be insufficient to perform regressions with the four types as regressors.

Table 1: Descriptive statistics

Variable	Obs	Avr	S.d.	Min	Max
ag_tractor	5190	163183.1	535339.5	2	5470000
atm	368	18318.39	43956.15	22.608	370782.8
aviationpkm	3535	7529.996	42396.95	0	772000
aviationtkm	3157	224.7141	904.3084	0	14788
cellphone	3963	1046050	7260919	0	2.06E+08
computer	1350	2943427	1.24E+07	4.097402	1.90E+08
elecprod	5991	5.27E+10	2.06E+11	100000	3.20E+12
internetuser	1446	1753685	9086197	0	1.59E+08
radio	5614	10305.62	43871.5	0	585000
railline	4584	11939.46	35181.85	0	361049
railpkm	3305	16487.33	51290.82	0	414000
railtkm	3667	58422.92	306202.9	0	3900000
shipton_steammotor	1752	3778.575	9293.092	7	81528
steel_bof	1412	9040.385	15971.17	4	100000
steel_eaf	2212	2714.221	5698.591	1	47850
telegram	2466	12.64869	24.44503	0	312.24
telephone	5255	3028552	1.40E+07	300	2.14E+08
tv	4728	5836445	2.50E+07	10	4.12E+08
vehicle_car	5095	2591432	1.32E+07	100	2.22E+08
vehicle_com	4710	725.3957	4750.137	0.1	88000
modern_techs_st_aug	10899	0	1.00174	-6.422771	12.23062
comm_techs_st_aug	10899	0	1.900109	-5.824181	12.35615
transport_techs_st_aug	10899	0	3.373964	-9.800905	32.98412
prod_techs_st_aug	10899	0	1.657976	-6.283744	11.1706
hc	6694	2.093233	0.6318047	1.018154	3.618748
Open	7760	0.4888119	0.6575676	2.93E-06	24.68241
lgini_st1	4597	2.747416	0.4281077	1.194536	3.80669

4 Estimation and Methods

Our baseline specification is as follows:

$$gini_{it} = \beta_{1i} Techh_{jit} + \beta_{2i} hc_{it} + \beta_{3i} Open_{it} + \lambda_i' \mathbf{f}_t + u_{it} \tag{3}$$

where *gini* is the natural logarithm of the uncertainty-corrected Gini coefficient given by (1), $Techh_{jit}$ is the measure of technology adoption given by (2), hc_{it} is the measure of human capital, and $Open_{it}$ is the measure of openness, all described above.[3] Thus the coefficient on

[3]Specification (3) is a logarithm version of the skill premium equation 1 in Acemoglu (2002a) $w = c\frac{\left(\frac{A_h h}{A_l l}\right)^{\frac{\sigma-1}{\sigma}}}{(h/l)}$, where $\left(\frac{A_h h}{A_l l}\right)$ is the skill complement technology adoption, h/l is the human capital ratio, σ the elasticity of substitution between both factors and c a constant. As discussed below, the specification is

our measure of technology β_{1i} measures the effect that a skill-complementary technology has on inequality or, in other words, the effect of technology on inequality that depends on the existing level of human capital. A positive coefficient means that a higher level of adoption of a given technology or a given type of technology causes a higher level of inequality, an influence that is dependent on human capital. Thus, higher levels of human capital enhance the effect of a given technology on inequality. If the coefficient is negative, the effect of the skill-complementary technology or type of technology tends to decrease inequality, which indicates that a higher level of adoption decreases inequality and this negative effect is enhanced by the existing level of human capital. This effect may be conditional on a direct effect of human capital, captured by β_{2i}. Yeaple (2005) support theorectically that openness may affect income inequality, specially when compared high skilled with median-skilled individuals. Empirically, Meschi and Vivarelli (2009) showed that trade with high income countries worsen income distribution in developing countries, through both imports and exports. Thus we also introduce openness in the regression, evaluating its marginal effect by the coefficient β_{3i}.

Finally, we may consider that technology adoption is being determined by the same phenomena as inequality, by common factors such as globalization or the entry of China into the world market and technology would thus become an endogenous variable. These common factors are accounted for in $\mathbf{f}_t$.[4] λ_i' is the vector of factor loadings associated with the common factors. As can be observed from (3) each coefficient is country-specific, thereby allowing for complete heterogeneity in the estimation. Additionally, as each regressor can also depend on the common factor, the method is in fact robust to endogeneity of the observable factors toward the common factors determining inequality. The estimation is performed using the Pesaran (2006) common factor estimator in the baseline analysis which also accommodate heterogeneous effects among different countries. As Pesaran and Tosetti (2011) explain, this method is robust to non-stationarity in both observable and non-observable variables and works well in the presence of weak and/or strong cross-sectionally correlated errors.

5 Results

In this section we begin by presenting and analyzing results for the influence of each technology on income inequality and then the results for the influence of the four technology-type measures.

5.1 Influence of 20 Different Technologies on Income Inequality

In this section we present regressions with specification (3) in which $Techh_{jit}$ assumes each of the 20 technologies considered by Comin et al. (2013).

In order to allow for a comparison with results without skill-complementary technologies, we first describe the results of a regression without them. In a regression in which only human capital (hc) and openness were considered (i.e. restricting $\beta_{1i} = 0$), human capital would be highly significant (p-value of 0.000) with a coefficient of 1.2, meaning that a change in human

enlarged to consider openness and common factors as determinants of inequality.

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

Table 2: Inequality and Technologies: Part I

Techh def.	(1) tt	(2) atm	(3) a1	(4) a2	(5) cp	(6) ct	(7) ep	(8) it	(9) ra	(10) r1
Techh	0.02	0.10	0.05	0.07*	0.03**	0.02	0.14**	0.07***	0.11	-0.14
	(0.89)	(0.30)	(0.38)	(0.07)	(0.04)	(0.65)	(0.03)	(0.00)	(0.44)	(0.65)
hc	-0.85	-2.33	0.34	0.68	0.95	1.22	-2.36	-1.06	-0.86	1.96
	(0.49)	(0.38)	(0.66)	(0.20)	(0.21)	(0.38)	(0.17)	(0.52)	(0.54)	(0.32)
Open	-0.01	-0.03	0.07	0.06	0.05	0.03	0.03	0.07	-0.01	-0.04
	(0.66)	(0.89)	(0.18)	(0.24)	(0.41)	(0.55)	(0.29)	(0.47)	(0.73)	(0.47)
Wald	0.69	1.84	2.79	6.37*	0.07*	1.32	7.84**	11.1**	1.10	1.73
Avr. Obs.	22.6	11.2	20.8	19.5	12.4	11.5	22.4	10.0	21.1	23.2
N. Countries	109	33	68	64	106	100	104	107	109	74
Total Obs.	2465	368	1415	1250	1314	1153	2326	1075	2304	1718

Note: Dependent Variables natural logarithm of the Gini coefficient. Definitions: tt - tractors; atm - ATM machines; a1 - aviation passengers; a2 - aviation cargo; cp - cellphones; ct-computers; ep- electricity production; ra- radios; r1 - length of rail lines. A constant is included in regressions but omitted from the table. Values in parentheses are p-values. P-values of coefficients are based on robust standard errors. Level of significance: *** for p-value<0.01; **for p-value<0.05;* for p-value<0.1. Lists of countries included in individual regressions are available upon request.

capital of 1% would raise the inequality index by 1.2%. Openness however would present a less significant effect of 0.032, with a significance level of only 19.5%. This regression would include 123 countries with a minimum of 4 and a maximum of 52 observations. The Wald test indicates the global significance of regressors.

Tables 2 and 3 present the results. Results indicate positive and significant effects of aviation, cell phones, electric production, internet, telephone and TV on income inequality. This broadly confirms the theoretical results according to which ICT and general purpose technologies (such as aviation and electricity) adoption tend to increase inequality. Quantitatively, significant elasticities are between 0.03 (cellphones) to 0.22 (telephones), meaning, e.g., that a 1% increase in the use of telephones will imply an increase in inequality of 0.22%, for a given level of human capital. Interestingly the introduction of skill-complementary technologies in the regressions implies that a direct effect of human capital almost disappears, with only four exceptions, columns (3), (5), (6), and (10) in Table 3.

5.2 Influence of Technology Types

In order to summarize results we built a taxonomy of four technology types, as described above. We now present the results for the influence of those technology types on inequality. This also allows us to analyze the conditional effect of each technology type on inequality, which enables answering the question if inequality rises due to e.g. ICT for the same adoption

Table 3: Inequality and Technologies: Part II

Techh def.	(1) r2	(2) r3	(3) sh	(4) s1	(5) s2	(6) tg	(7) tl	(8) tv	(9) cr	(10) tr
Techh	0.08	-0.04	0.06	0.03	0.00	-0.09	0.22**	0.18**	0.11	0.06
	(0.39)	(0.52)	(0.67)	(0.30)	(0.90)	(0.15)	(0.05)	(0.02)	(0.20)	(0.35)
hc	1.04	0.87	1.67*	0.85	1.13*	1.80***	-0.60	-1.33	0.52	1.49**
	(0.19)	(0.17)	(0.07)	(0.15)	(0.08)	(0.0)	(0.76)	(0.30)	(0.64)	(0.02)
Open	0.09	-0.00	-0.07	-0.02	0.12***	0.02	0.06	-0.01	0.03	0.03
	(0.10)	(0.95)	(0.25)	(0.77)	(0.01)	(0.54)	(0.11)	(0.78)	(0.48)	(0.52)
Wald	5.12	2.26	4.97	3.20	9.86**	12.1***	6.72*	7.23*	2.35	6.83*
Avr. Obs.	20.8	21.1	21.6	23.9	22.9	20.8	18.5	21.6	20.6	22.6
N. Countries	59	64	39	47	71	49	104	111	99	77
Total Obs.	1229	1353	843	1124	1624	1021	1929	2402	2038	1742

Note: Dependent Variables natural logarithm of the Gini coefficient. Definitions: r2 - railway passengers; r3 - railway cargo; sh - ships; s1 - steel in blast oxygen furnaces; s2 - steel in electric arc furnaces; tg - telegrams; tl- telephones; tv- televisions; cr- passenger vehicles; tr - commercial vehicles. A constant is included in regressions but omitted from the table. Values in parentheses are p-values. P-values of coefficients are based on robust standard errors. Level of significance: *** for p-value<0.01; **for p-value<0.05;* for p-value<0.1. Lists of countries included in individual regressions are available upon request.

of other technology types. Thus, $Techh_{jit}$ now assumes one of the four types: modern ICT, older ICT, production, or transportation.

We continue to employ Pesaran (2006) common correlated effects estimator but we also implement slightly modified common correlated effects estimators suggested in recent literature. We include in the regressions one or more additional covariates in the form of cross-section averages, which helps to identify the unobserved common factors (in the spirit of Pesaran et al. (2013) and following what Eberhardt and Presbitero (2014) did in an empirical implementation). To this end, we consider openness as a cross-section average, seeking to identify the unobserved common factors as linked with globalization and global integration (e.g. the entrance of China in global markets affecting all the countries). In some of the regressions, together with openness we also considered averaged TFP as an additional control. This is to identify the unobserved common factors also with productivity spillovers around the world. Given that we now have available several more time-series observations *per* country, we present specifications with country trends, as well as information on their significance across countries. Table 4 presents these results.

Results indicate a highly significant effect of transportation technologies adoption on the increase of inequality, conditional on the adoption of other technology types. Thus, it seems that countries that adopted more transportation technologies than other technologies have also faced, due to that, an increase in inequality. This is a somewhat unexpected result, as theory has focused more on information and communication technologies as a source of inequality. Countries that adopted more transportation technology may be highly integrated in world trade and thus be highly competitive. This can influence the wages of the most adaptable workers and thus increase inequality. In fact, transportation technologies are general purpose technologies in the sense that they are applied to the economy as a whole, with important effects on sectoral and countries integration. Results also reveal positive effects of older ICT technologies (specifications (2) and (4)) and of production technologies (specification (1)). Curiously, modern ICT has a non-significant effect on inequality, conditional on other technology-types adoption. Quantitatively, the effects mean that a 1 standard-deviation increase in a skill-complementary transportation technology (s.e.=3.37) would increase inequality by 3.37% to 6.74%. If the 1 standard-deviation rise occurs in the older ICT technologies (when significant), for a s.e. equal to 1.90, the implied rise in inequality will amount to a value between 1.90% and 3.80%. Finally, If the 1 standard-deviation rise occurs in the production technologies (when significant), for a s.e. equal to 1.66, the implied rise in inequality will amount to 3.32%.

It is interesting to evaluate if these results differ from rich countries to poor countries, even before we analyze effects by individual country. Several features that could influence the relationship between skill-complementary technologies and inequality are quite different between rich and poor countries. The level of education, the composition between general and vocational education, and the proximity to the technology leader are only some of them. We next present results in which we divided the sample by the average GDP *per capita*, after averaging GDP *per capita* inside each country. Results shown in Table 5 highlight that the robust effects described above are all due to very strong positive effects of the technology types adoption that occur in rich countries. In fact, in rich countries, both transportation technologies and old ICT adoption are associated with high inequality and also modern ICT causes inequality when a trend is considered (column (2)), confirming the theory result and

Table 4: Inequality and Technology-types

	(1)	(2)	(3)	(4)	(5)	(6)
Modern ICT	0.00	0.00	0.00	-0.00	-0.00	-0.00
	(0.895)	(0.494)	(0.931)	(0.740)	(0.935)	(0.905)
Older ICT	0.01	0.01**	0.01	0.02*	0.01	0.01
	(0.223)	(0.032)	(0.223)	(0.089)	(0.417)	(0.395)
Production	0.02***	0.01	0.01	0.01	0.00	-0.01
	(0.008)	(0.172)	(0.369)	(0.365)	(0.812)	(0.568)
Transportation	0.01*	0.01**	0.02***	0.02***	0.02***	0.02***
	(0.052)	(0.016)	(0.001)	(0.003)	(0.004)	(0.007)
Trend	–	-0.01***	–	0.01**	–	0.00
		(0.009)		(0.047)		(0.988)
Additional CS Avg	No	No	Open	Open	Open; TFP	Open; TFP
% sig. trends	–	32.3%	–	25.9%	–	27.5%
Wald	9.12*	12.81**	92.04***	80.86***	76.41**	56.93***
Avr. Obs.	29.2	29.4	32.2	32.7	32.7	33.3
N. Countries	156	155	115	112	112	109
Total Obs.	4558	4552	3702	3666	3666	3627

Note: Dependent Variables natural logarithm of the Gini coefficient. A constant is included in regressions but omitted from the Table. Values between parentheses are p-values. P-values on coefficients are based on robust standard errors. Level of significance: *** for p-value<0.01; **for p-value<0.05;* for p-value<0.1. Additional CS Avg means the additional variables added as controls as cross-section averages. % sig. trends is the percentage of country-trends that are statistically significant at the 5% level. Lists of countries included in individual regressions are available upon request.

existing evidence relating ICT to inequality (e.g. in Jaumotte et al. (2013)). In the sample of the poorest countries, it is not possible to identify any significant effect of skill-complementary technology on inequality.

5.3 Robustness

We have also tested our results against differences in the implemented estimator and in a restricted sample. The alternative estimator was developed by Eberhardt and Teal (2010), seeking to identify the common unobserved effects with a single common factor designed to estimate a residual such as TFP. The restricted sample is one with higher populated time-series in which we restricted the sample to the countries that had more than 15 time-series observations for the dependent variable.

Generally, the robustness analysis presented in Table 6 confirms our previous results. Transportation technology increases inequality throughout all the considered specifications with similar quantitative effects as those obtained previously. Additionally older ICT also contributes to the rise in inequality in specifications in which a (statistically significant) trend is introduced in the regression. The specifications based on the Eberhardt and Teal (2010) estimator

Table 5: Inequality and Technology-types: Rich and Poor Countries

	(1)	(2)	(3)	(4)
	Rich		Poor	
Modern ICT	0.01	0.02**	-0.00	0.00
	(0.310)	(0.042)	(0.711)	(1.000)
Older ICT	0.01**	0.01**	-0.00	0.00
	(0.024)	(0.023)	(0.787)	(0.676)
Production	0.00	0.00	-0.00	0.01
	(0.969)	(0.980)	(0.943)	(0.307)
Transportation	0.01**	0.01***	-0.00	-0.00
	(0.019)	(0.009)	(0.601)	(0.911)
Trend	–	0.00	–	-0.01***
		(0.166)		(0.004)
% sig. trends	–	33.8%	–	25.6%
Wald	11.59**	15.51**	0.49	1.23
Avr. Obs.	33.4	33.8	26.1	26.1
N. Countries	66	65	90	90
Total Obs.	2205	2199	2353	2353

Note: Dependent Variables natural logarithm of the Gini coefficient. Values in parentheses are p-values. A constant is included in regressions but omitted from the table. P-values of coefficients are based on robust standard errors. Level of significance: *** for p-value<0.01; **for p-value<0.05;* for p-value<0.1. Additional CS Avg means the additional variables added as controls as cross-section averages. % sig. trends is the percentage of country-trends that are statistically significant at the 5% level.

tend to increase the positive effect of modern ICT and in the specification with a (statistically significant) trend - column (4) - it also becomes highly significant. We have also divided the sample between rich and poor countries as we did before and use the Eberhardt and Teal (2010) estimator.[5] Besides the significant effects obtained in the rich countries sample presented in Table 5, we have also obtained for the poor countries positive and highly significant (2.2% and 6.9% levels of significance respectively) coefficients for new and old ICT.

We performed an additional test on all results (which we do not show but are available upon request). Until now our measure of skill-complementary technology is a measure affected by scale, i.e., technological adoption is taken as total technological adoption, thus being influenced by the size of the country. This does not raise any particular problem *de per si*, since the inequality index is independent of the size of the country as well as human capital and openness. The conclusion is that some of those skill-complementary technology adoption affected by scale tend to influence inequality rises. Does an alternative *per capita* skill-complementary technology adoption measure which would be scale-independent have the same effect on inequality? We re-ran all the regressions in the paper with these alternative measures (consisting of dividing the measure in (2) by the population in each year and country). Conclusions are as follows:

- Cellphone, internet, telephone, and TV adoption cause more inequality in specifications similar to those in Tables 2 and 3;
- Telegraph adoption contributes to decrease inequality in specifications similar to those in Tables 2 and 3;
- Transportation, production, and older ICT are still significant as determinants of (more) inequality in several regressions specified as in Table 4;
- Transportation technologies and modern ICT are still responsible for higher inequality in rich countries, as specified in Table 5;
- Production technologies and older ICT are significant determinants in the Pesaran (2006) specification, in specifications similar to those in Table 6;
- Older ICT is the only significant determinant of higher inequality in the Eberhardt and Teal (2010) specification, in a specification similar to that in Table 6.

Thus, surprisingly, despite a complete re-definition of the relevant measures for skill-complementary technologies adoption, removing the scale dimension of variables, results are quite consistent to those obtained when using the scale affected measure of skill-complementary technology adoption. When technology-types measures are considered, production technologies become relatively more important in explaining higher levels of inequality than before, maintaining the relative importance of transportation, old, and modern ICT.

Finally, we wish to discuss a possible alternative to construct the measures of technology types. Alternatively to what has been done, we could have restricted the technology types measures on observations for which all the components presented non-missing values. Due to the fact that this sample is highly unbalanced, doing so would imply very few observations

[5] These results are not presented but are available upon request.

Table 6: Inequality and Technology-types: Robustness Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
Estimator	Eberhardt and Teal (2010)	Eberhardt and Teal (2010)	Eberhardt and Teal (2010)	Eberhardt and Teal (2010)	Pesaran (2006)	Pesaran (2006)
Sample	Total		Highly Populated Time-Series (≥ 15)			
Modern ICT	0.00	0.00	0.00	0.01**	-0.00	0.00
	(0.571)	(0.126)	(0.469)	(0.050)	(0.801)	(0.881)
Older ICT	0.00	0.01***	0.01	0.01***	0.01	0.02**
	(0.450)	(0.005)	(0.296)	(0.004)	(0.160)	(0.026)
Production	-0.00	-0.00	-0.01	0.00	0.02*	0.01
	(0.262)	(0.800)	(0.135)	(0.968)	(0.092)	(0.273)
Transportation	0.01*	0.01**	0.01**	0.01**	0.01*	0.01**
	(0.082)	(0.039)	(0.039)	(0.023)	(0.072)	(0.037)
Trend	–	0.00**	–	0.00***	–	-0.00*
		(0.021)		(0.009)		(0.099)
% sig. trends	–	42.4%	–	44.3%	–	35.1%
Wald	5.17	14.48***	8.13*	17.39***	8.12*	10.52**
Avr. Obs.	29.4	30.0	32.8	32.8	32.8	32.8
N. Countries	155	151	131	131	131	131
Total Obs.	4552	4524	4301	4301	4301	4301

Note: Dependent Variables natural logarithm of the Gini coefficient. A constant is included in regressions but omitted from the table. Values in parentheses are p-values. P-values of coefficients are based on robust standard errors. Level of significance: *** for p-value <0.01; **for p-value<0.05;* for p-value<0.1. Additional CS Avg means the additional variables added as controls as cross-section averages. % sig. trends is the percentage of country-trends that are statistically significant at the 5% level.

for the technology types variables which would imply that a regression with the four variables as regressors would simply not be possible. However, it would be possible to evaluate the (non-conditional) effect of each technology type to evaluate if, for example, it is crucially different from the conditional one. Interestingly, when testing individually the technology-types variables (restricted to non-missing observations in all the components), despite a huge drop in the number of observations (from nearly 4500 as in Table 6 to around 500), all the technology-types have highly significant and positive coefficients (at 1% level), with coefficients oscillating from nearly 0.06 for all technology-types except older ICT type, and 0.14 for older ICT type, highlighting also positive and significant effects for those restricted measures for technology-types.

6 Conclusion

Quantitative assessments of the determinants of inequality are scarce. So are the quantitative evaluations of the theories that assume that skills are complementary to technologies and jointly determine the evolution of inequality. In this work we seek to contribute to enrich that literature. To this end, we use very recent data on the Gini index, available for a wide range of countries and years and relate it with measures of skill-complementary technological adoption of 20 different technologies. First, we analyze each skill-complementary technology and evaluate its effect on inequality. We discovered that several skill-complementary technologies contribute to the inequality rise and none contribute to the inequality drop. Adoption of technologies such as aviation, cell phones, electricity production, internet, telephone, and TV, contribute to increase inequality. Then, we construct four different measures of technology-types allowing us to evaluate the conditional contribution of each type to the evolution of inequality. We found strong evidence that older ICT and transport technologies (and less frequently modern ICT) tend to increase inequality. Thus, earlier emphasis in the literature on the effect of ICT in raising inequality is relatively shaken by our results, as modern ICT adoption is definitively not the most significant type of technology adoption in raising inequality. We also discovered that results are much stronger in rich countries than in poor. The use of heterogenous panel estimators allowed us to highlight the diversity of results among countries. Nevertheless, an overwhelming number of countries present an influence of increased skill-complementary technological adoption (mainly in older ICT and transportation technologies) on the increase of inequality.

Our results are robust to a series of modifications in specification, estimator, samples, and to the skill-complementary technological adoption measure.

These results may have policy implications for the design of incentives for adopting technologies, especially for rich and well human-capital-endowed countries, in which the effect in the rise of inequality may be quite significant. In particular, fiscal redistributive policy or poverty relieving fiscal measures may have a crucial role in times of high rates of adoption.

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A Appendix

A.1 Results by Country

This section reports the results by individual country. For this we consider the restricted sample with high populated time-series considered also in Table 6. This is done in order to maximize time-series availability within countries. Tables 7, 8, and 9 show the statistically significant results by country.

Table 7: Countries statistically significant - Part 1

Countries	modern ICT	old ICT	transportation	production
Argentina				0.10 (0.000)
Armenia		-0.27(0.000)		
Australia			0.03(0.007)	
Bolivia	0.29(0.005)	0.55(0.018)	-1.51(0.000)	4.866(0.003)
Botswana	-0.20(0.090)			
Brazil			0.17(0.094)	
Bulgaria		0.19(0.001)		-0.37(0.000)
Burkina Faso				
Burundi	-0.03(0.001)		0.09(0.000)	0.15(0.000)
Cambodia		-0.94(0.057)		
Cameroon				1.54(0.003)
Canada		-0.06(0.034)		0.08(0.000)
Chile			0.22(0.000)	-0.20(0.003)
China			0.07(0.008)	0.16(0.020)
Costa Rica		-0.57(0.030)		
Czech Republic	0.11(0.006)	0.06(0.099)	0.03(0.003)	-0.10(0.068)
Dominican Republic			0.46(0.072)	
Ecuador	-0.14(0.087)			
Egypt			0.14(0.008)	-0.07(0.045)
Estonia	0.33(0.004)			
France		0.11(0.015)	-0.03(0.030)	
Ghana			0.32(0.019)	
Guatemala			0.11(0.001)	
Haiti			-2.04(0.017)	
Hong Kong			0.14(0.039)	-0.26(0.096)

These results highlight the great heterogeneity of the effects of technology adoption on income inequality by country. Despite some globally non-significant signs, there might be a wide range of countries in which technological adoption tends to decrease or increase inequality. Additionally, despite the overall positive signs of the skill-complementary technological adoption coefficients, there might be some countries in which there is evidence that technological adoption decreases inequality.

Of the 131 countries entering in regressions (see e.g. columns (3) to (6) in Table 6), there are 75 with significant coefficients in at least one technology-type. As expected, most of

Table 8: Countries statistically significant - Part 2

Countries	modern ICT	old ICT	transportation	production
Hungary	0.18(0.037)	-0.09(0.054)	0.11(0.015)	
Iceland	-0.33(0.003)		0.16(0.034)	
Indonesia	0.25(0.000)			
Iran		0.17(0.070)		
Ireland			0.16(0.000)	-0.08(0.078)
Israel				0.67(0.077)
Japan	-0.03(0.074)			
Jordan	-0.18(0.008)	0.31(0.068)		
Kenya	-0.19(0.043)			
Korea, Republic of			0.100(0.009)	
Kyrgyz Republic		0.33(0.046)		
Lao				0.90(0.026)
Latvia		-0.07(0.048)	0.133(0.028)	
Luxembourg				0.22(0.045)
Malawi		0.12(0.024)		
Malaysia			0.30(0.000)	
Mali		0.26(0.048)		
Mauritius				-0.28(0.000)
Mexico		0.12(0.002)		
Moldova		0.12(0.005)	-0.31(0.006)	0.25(0.000)
Morocco		-0.16(0.062)		
Netherlands	0.06(0.044)	0.09(0.008)		-0.12(0.051)
Norway				0.07(0.031)
Pakistan			-0.31(0.000)	-0.14(0.089)
Panama		0.27(0.016)		0.39 (0.018)

the countries present positive signs, i.e., technology adoption causes higher inequality. There are 11 countries in which modern ICT adoption tends to raise inequality and 8 in which this technology type tends to decrease inequality. Among the first group, we find countries such as Netherlands, Iceland, United Kingdom, Thailand and Indonesia. Among the second, we identify countries like Switzerland, Japan, Burundi and Equador. There are many more countries with significant coefficients associated with other technology types than to modern ICT (29 to old ICT and transportation type and 34 to production type). There are 22 countries in which old ICT adoption tends to raise inequality and 7 in which this technology type tends to decrease inequality. Among the first group, we find countries such as France, Netherlands, Singapore, Sweden, Iran, Panama, Mali, and Malawi, to give some examples. Among the second, we identify countries such as Canada, Latvia, Cambodia and Costa Rica. There are 24 countries in which transportation technology-type adoption tends to raise inequality and 6 in which this technology type tends to decrease inequality. Among the first group, we find countries such as Australia, Iceland, Ireland, Burundi, China, Tanzania, and Thailand. The second group comprises Bolivia, France, Haiti, Moldova, Pakistan, and Ukraine. Despite the

Table 9: Countries statistically significant - Part 3

Countries	modern ICT	old ICT	transportation	production
Paraguay				0.11(0.061)
Peru	0.30(0.012)			
Poland				0.27(0.019)
Portugal				-0.21(0.097)
Romania				-0.31(0.000)
Russian Federation		0.15(0.014)		-0.11(0.032)
Sierra Leone			0.21(0.000)	
Singapore		0.07(0.093)		
South Africa			0.08(0.086)	-0.26(0.000)
Spain				0.19(0.014)
Sri Lanka			0.21(0.001)	
Sweden		0.03(0.087)		
Switzerland	-0.13(0.002)			0.05(0.040)
Taiwan				0.14(0.012)
Tajikistan	0.13(0.062)	0.14(0.000)		
Tanzania			0.42(0.001)	
Thailand	0.17(0.006)	0.37(0.002)	0.21(0.004)	-0.34(0.003)
Uganda		0.72(0.000)		
Ukraine		0.15(0.020)	-0.510(0.000)	
United Kingdom	0.05(0.010)			
Uruguay	0.16(0.046)		0.32(0.001)	
Venezuela		0.19(0.002)	0.09(0.011)	-0.23(0.000)
Yugoslavia		1.49(0.032)		-1.59(0.017)
Zambia				0.87(0.002)

generally non-significant coefficient for the production-type technology adoption (see Tables 4 and 6), this is the technology-type with the highest number of significant coefficients *per* country (34). However, the number of negatively significant coefficients (16) is relatively close to the number of positively significant coefficients (18). Countries with a significantly positive sign for the production technology-type coefficient are, e.g., Argentina, Bolivia, Israel, Poland, and Spain. Countries with a significantly negative sign for the production technology-type coefficient are, e.g., Bulgaria, Chile, Hong-Kong, Pakistan, and Portugal. This means that despite the fact that a positive effect of some types of technology adoption in raising inequality was obtained for the panel database, mainly for the rich countries (see Table 5), it is undoubted that we can identify both rich and poor countries with significantly positive signs and with significantly negative signs.

A.2 List of Technologies and Abbreviations

- wheel and crawler tractors (excluding garden tractors); definition in the source: tractor; abbreviation: tt

- electromechanical devices that permit authorized users, typically using machine readable plastic cards, to withdraw cash from their accounts and/or access other services; definition in the source: atm; abbreviation: atm
- Civil aviation passenger-KM traveled on scheduled services by companies registered in the country concerned. Not a measure of travel through a country airports; definition in the source: aviationpkm; abbreviation: a1
- Civil aviation ton-KM of cargo carried on scheduled services by companies registered in the country concerned. Not a measure of travel through a country's airports; definition in the source: aviationtkm; abbreviation: a2
- Number of users of portable cell phones; definition in the source: cell phone; abbreviation: cp
- Number of self-contained computers designed for use by one person; definition in the source: computer; abbreviation: ct
- Gross output of electric energy (inclusive of electricity consumed in power stations) in KwHr; definition in the source: elecprod; abbreviation: ep
- access to the worldwide network; definition in the source: internetuser; abbreviation: it
- Number of Radios; definition in the source: radio; abbreviation: ra
- Geographical/route lengths of line open at the end of the year. Narrow gauge lines generally included, but mountain railways, purely industrial lines not open to the public, and urban systems generally excluded; definition in the source: railline; abbreviation: r1
- Passenger journeys by railway in passenger-KM. Free passengers typically excluded but may be included for some countries; definition in the source: railpkm; abbreviation: r2
- freight carried on railways (excluding livestock and passenger baggage). Freight for servicing of railroads is typically excluded but may be included for some countries; definition in the source: railtkm; abbreviation: r3
- steamships (above a minimum weight) in use at midyear; definition in the source: shipton-steammotor; abbreviation: sh
- Crude steel production (in metric tons) in blast oxygen furnaces (a process that replaced Bessemer and OHF processes); definition in the source: steel-bof; abbreviation: s1
- Crude steel production (in metric tons) in electric arc furnaces (a process that complemented and improved upon Bessemer and OHF processes); definition in the source: steel-eaf; abbreviation: s2
- Telegrams; definition in the source: telegram; abbreviation: tg
- mainline telephone lines connecting a customer's equipment to the public switched telephone network as of year end; definition in the source: telephone; abreviation: tl

- television sets in use; definition in the source: tv; abbreviation: tv
- passenger cars (excluding tractors and similar vehicles) in use. Numbers typically derived from registration and licensing records, meaning that vehicles out of use may occasionally be included.; definition in the source: vehicle-car; abbreviation: cr
- commercial vehicles, typically including buses and taxis (excluding tractors and similar vehicles), in use. Numbers typically derived from registration and licensing records, meaning that vehicles out of use may occasionally be included; definition in the source: vehicle-com; abbreviation: tr