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Technological change, rent and income inequalities: A Schumpeterian approach

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ABSTRACT

Increasing levels of income inequality have recently attracted much attention. The literature has concentrated on the hypothesis that increasing levels of income inequality are the cause of slow growth and social unbalances. This paper contributes to exploring an alternative hypothesis according to which increasing levels of income inequality are the consequence, rather than the cause, of slow growth and more specifically of the slowing pace of technological change. The paper articulates the Schumpeterian hypothesis that the rate of technological change exerts a significant influence in reducing income distribution. Due to the powerful effects of creative destruction, the rate of technological change engenders a reduction in wealth and rent inequalities that are highly skewed and, consequently, limits income inequality. We test this hypothesis in an empirical exercise by implementing quantile regressions on a large dataset of advanced and industrializing economies. The inequality diminishing effect of technological change holds along the entire income inequality distribution, but exhibits larger effects in countries where the concentration of wealth and, consequently, income asymmetries are stronger. These results have novel welfare implications and suggest some crucial insights for economic policy analysis.

1. Introduction

The literature on the causes and consequences of income inequality has been growing steadily (see the recent contributions by Aghion et al. (1999) and Piketty (2014)). A great deal of empirical evidence reveals episodes of increasing income inequality both in advanced and industrializing countries since the end of the 20th century (Aghion et al., 1999; Kaplan and Rauh, 2010). One of its valuable achievements is the identification of specific dimensions of income inequality. It is now common to distinguish between functional inequality (i.e. the division of income between capital rents and labour remuneration in an economy) and personal inequality (i.e. the income differences across households, regardless of the nature of their assets/holdings). The concept of personal inequality can be further refined into income inequality – where income refers both to wage income and to other income sources such as rents – and wage inequality (cf. the typology elaborated by Aghion et al., 1999; Piketty and Saez, 2003).[1]

More recently, contributions by Thomas Piketty and Anthony Atkinson have drawn attention to the role of income inequality as a determinant in the reduction in the pace of economic growth (Atkinson and Piketty, 2007 and 2009; Piketty, 2014). An inclusive review of the literature by Franzini and Pianta (2016) effectively summarizes the basic argument according to which the raising levels of income inequality have direct negative consequences that include both: i) the negative economic effects stemming from a decline in marginal propensity to consumption and the accumulation of financial capital (Atkinson, 2015), and ii) relevant socioeconomic aspects in terms of inequality of opportunities (Ramos and Van de Gaer, 2015) and reduction in happiness (Ferrer-i-Carbonell and Ramos, 2014). An increasing awareness of such negative consequences, both economic and societal, draws attention to the identification of determinants of income inequality as the necessary condition for defining appropriate economic policy aimed at limiting its impact.

We contribute to this literature by exploring the determinants of income inequality rather than its effects: income inequality is the consequence of slow growth, rather than its cause. More specifically, we draw attention to the role of technological change in assessing the levels of income inequality and we put forward and test the hypothesis that the increasing levels of income inequality are determined by the decreasing pace of technological change.

Whereas some important work has been done on the effects of the *direction* of technological change (see, for instance, Acemoglu (2003),

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[1] As a matter of fact, Aghion et al. (1999) discuss wealth instead of income inequality, the former referring to the stock of income possessed by households. At the same time, they acknowledge that data on the distribution of wealth are absent and researchers (including the authors of this paper) are forced to proxy wealth with income distribution. Nevertheless, both measures generally report a similar path of cross-sectional variation (Aghion et al., 1999).

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Autor et al. (2008), and Galor and Moav (2000)), and whether it is labour or capital saving, quite surprisingly, little attention has been paid to appreciating the role of technological change in general, namely, in influencing income distribution between capital and labour via its powerful effects on rent inequalities. Much work in the field has focused on the distribution of income within countries. The comparative approach based on the analysis of the changes in income distribution across countries has received less attention. However, this approach seems to be the most promising for studying the effects of technological change in countries with different levels of income asymmetry.

We fill this gap both on the theoretical and empirical side. A comprehensive reappraisal of the Schumpeterian legacy shows that technological change affects income inequality, not only via a reduction in wage inequalities, but also in rent inequality, a key component of income inequality. More precisely, we analyse in depth the mechanisms through which the rate of introduction of innovations is expected to reduce wealth inequality via the creative destruction of large portions of the existing capital stock, and its effects in terms of rent inequality via a reduction in both extra profits and interest rates. To this end, we assume a comparative approach that includes a variety of countries. The stylized fact of the global decline of labour share (Karabarbounis and Neiman, 2014) makes our focus on rent inequality all the more relevant.

To test our hypothesis, we use the quantile regression framework to verify whether the established relationship between technological change and income inequality holds for different quantiles of cross-country inequality distribution. The implications of our arguments lead us to expect that a reduction in mean inequality – due to the rates of introduction of innovations – takes place across all countries, but is driven by countries with relatively more asymmetric income distribution.

The choice of the quantile regression methodology justifies the selection of a wide sample of countries characterized by a controlled variance such that all the key parameters such as revenue levels, income concentration and rates of technological change exhibit acceptable levers. The set of countries selected using this methodology includes a reliable group of industrializing countries comprising Turkey, Brazil, Russia, India, and China, as well as the industrializing countries of Eastern Europe, alongside the traditional set of advanced countries (the advanced European countries, in addition to USA, Canada, Japan, Norway, Switzerland and Iceland). It excludes countries that do not seem able to command technological change. As a consequence, developing countries with high levels of income asymmetries are not taken into account.

Although quantile regressions have been sometimes used on a microeconomic level (e.g. Martins and Pereira (2004) and Fournier and Koske (2012)), this methodology has not been applied before to study income inequality at the macro-level.[2] Our results clearly confirm that – conditioning or not on country fixed effects – the introduction of innovation is a powerful factor in reducing income inequality.

The rest of the paper is structured as follows. Section 2 explores the literature on the relations between economic growth and income distribution and Section 3 articulates the main hypothesis. Section 4 presents the data set and methodology and discusses the results of econometric investigations and the final section summarizes the paper and elaborates policy implications.

2. Economic growth and income inequality

The path breaking contribution of Simon Kuznets (1955, 1963) remains the basic reference in the economics of income distribution for many reasons. Kuznets elaborated an interpretative framework in which the dynamics of income allocation reflect the changing distribution of wealth and skills and their changing prices with respect to standard labour. Kuznets, indeed, paid much attention to the changing structure of the economic systems at the time of industrialization, with a rapid shift away from an agricultural and rural economy towards an urban and industrial one.

In such a historical background, he identified an inverted-U relationship between economic development and income inequality. He noted that, in the early phases of industrialization, income inequality increases because of large differences in factor productivity between rural and urban activities. Radical structural changes increase income asymmetry since they engender a discontinuity in the social and economic organization. Income inequality, however, eventually declines with completion of the industrial transformation. Once the full system completes the industrial transformation, the standard dynamics of economic growth favour a reduction in income inequality along the following chain of factors: 1) savings increase the supply of capital 2) they decrease the levels of interest rates; 3) capital intensity increases and 4) labour productivity increases (with the appropriate supply of complementary skilled workforce), 5) leading to higher wages that make a larger supply of savings possible. Moreover, in an advanced industrial economy, tighter competition in product and factor markets makes it possible to minimize monopolistic profits. Following his chain of factors, it appears clear that the standard mechanism of economic growth reduces inequality (both income and wage) by means of a decrease in interest rates, a reduction in monopoly profits and an increase in wages. Hence, the famous inverted U-shaped relationship between inequality and revenue per capita, initially suggested by Kuznets (1963), acquires a fresh understanding. Quite surprisingly, however, Kuznets does not include technological change as a key aspect of economic growth and consequently a powerful factor in the reduction of income asymmetry.

The empirical literature provides contrasting evidence on the issue. The inverted U-shaped relationship between the stage of development and inequality finds only partial support and seems to be quite sensitive to the composition of the datasets and the time periods analysed (Adelman and Robinson, 1989; Atkinson and Piketty, 2007 and 2009). Dollar and Kraay (2002) conclude their inclusive study, extended to all countries of the Penn World Tables, that there is no systematic evidence confirming economic effects of growth on income distribution. There is, on the other hand, converging evidence on the positive effects of economic growth on a reduction in income inequality, especially in developing countries (Adams, 2002 and 2004; Adams and Page, 2003; Chen and Ravallion, 2001; Ravallion, 1995). The evidence regarding advanced countries is on the contrary mixed, especially when the last decade of the 20th century is considered (Atkinson and Piketty, 2009). As a matter of fact, Kaplan and Rauh (2010) show that income inequality has increased at a time of fast economic growth in the recent past. The evidence gathered by Gordon (2000 and 2012), however, may suggest that slow rates of innovation that have characterized the more recent years after the phase of a great burst of inventions in the 1970s are at the origin of the new increase in income asymmetry experienced in the last decades. A reduction in the rate of technological change would be the cause of an increase in income asymmetries (see Table 1 in the next section).

The later theoretical literature on the topic has shared the basic intuitions that support Kuznets' analysis. By articulating and expanding his basic hypothesis, theoretical models show consensus on the fact that in the long run, economic growth reduces income inequality. This result is much dependent on the working of equilibrium conditions. Accordingly, the closer the working of product and factor markets - including labour and financial markets - towards perfectly competitive equilibrium, the lower is income inequality (Hertel and Zhai, 2006). When economic growth is associated with market imperfections, income asymmetry will actually increase.

[2] Martins and Pereira (2004) use survey data for male workers and apply quantile regressions to analyse the relation between schooling and wage inequality in 16 countries in the mid-1990s. Fournier and Koske (2012) use conditional and unconditional quantile regressions to study determinants of labour earnings inequality based on household surveys.

Table 1
Unit cost of knowledge and total factor productivity (TFP) growth in OECD countries, 1985–2010.

Country	Unit cost of knowledge			TFP growth		
	1985–2010	1985–1998	1999–2010	1985–2010	1985–1998	1999–2010
Australia	0.5	0.5	0.6	0.9	1.1	0.5
Austria	1.8	1.1	2.6	1.4	1.3	1.4
Belgium	6.2	3.4	9.0	0.8	1.2	0.3
Canada	0.5	0.4	0.6	0.4	0.2	0.5
Denmark	1.7	1.1	2.5	0.8	1.1	0.3
Finland	1.5	0.6	2.6	1.8	2.2	1.2
France	2.1	1.9	2.4	1.0	1.4	0.6
Germany	1.1	1.1	1.1	0.9	1.2	0.7
Ireland	1.3	0.5	2.1	2.7	3.5	1.8
Italy	1.8	1.6	2.0	0.4	1.0	−0.3
Japan	0.3	0.3	0.3	1.4	1.8	0.9
Korea	0.2	0.3	0.2	3.8	4.3	3.3
Netherlands	3.4	2.9	3.9	1.0	0.9	1.1
New Zealand	0.2	0.1	0.2	0.5	0.5	0.4
Portugal	5.5	2.6	8.8	1.3	2.5	0.6
Spain	2.8	1.9	3.9	0.5	1.0	−0.1
Sweden	2.5	1.3	3.4	0.9	0.7	1.2
Switzerland	2.3	1.4	3.4	0.0	−0.6	0.4
UK	1.1	0.9	1.3	0.8	0.8	0.7
US	1.1	1.3	0.9	1.1	0.9	1.4
Average OECD	1.9	1.3	2.6	1.1	1.4	0.8

Note: Unit cost of knowledge is calculated as a share of R&D expenditure in millions of constant (2005) PPP dollars over the number of patent applications at the World Intellectual Property Organization (WIPO). TFP growth is the growth rate of multi-factor productivity in per cent.
Source: Antonelli and Gehringer (2016).

These results stem directly from an appreciation of the factors that account for economic growth in the standard framework. According to traditional growth theory, in fact, economic growth is engendered by the increasing stock of capital which takes place via the accumulation of savings. All imperfections in financial markets have strong negative effects on the correct allocation of resources, provoking inefficiency that favours income distribution among the wealthy (Aghion and Bolton, 1992). Measures that remove frictions from the financial markets and, hence, improve the availability and efficiency of capital for given levels of savings, are likely to favour a reduction in interest rates, and finally, an increase in capital intensity. The consequences for a reduction in wealth are straightforward: a reduction in interest rates shrinks the effects of the possible - actually frequent - asymmetries in the distribution of wealth that are, in relative terms, further reduced by an increase in wage levels (Beck et al., 2007).

Within the same interpretative framework, it is clear that an increase in competition both in domestic and international product markets is likely to affect the rates of economic growth positively with a possible reduction in income inequality. This works through a more efficient allocation of resources, an improved division of labour, as well as specialization, a growth in revenues, an increased abundance of capital, a reduction in capital rental costs, a reduction in the effects of wealth on income and, finally, an increase in wages (Aghion and Bolton, 1992 and 1997).

The exposure to international competition is especially effective in reducing and sometimes overcoming the barriers to entry and mobility. Such barriers limit competition in the domestic markets, and consequently, overall growth dynamics. Greater foreign competition, visible through the increase in imports, makes markups decline and, thus, also profit margins fall (Chen et al., 2009). Large empirical evidence confirms a positive relationship between the share of imports to GDP and competition (e.g. MacDonald, 1996). However, the relationship has been found effective for exports too. More precisely, the larger the shares of exports to GDP, the higher the levels of international competition and the closer the conditions of product markets to the standards of workable - if not perfect - competition. It is consequently clear that the larger levels of openness to trade - as measured in terms of the share of imports and exports to GDP - are, the closer the levels of prices to minimum average costs and the lower the levels of mark-ups and quasi rents. Low levels of mark-ups and quasi-rents ensure that the distribution of income is close to competitive levels, with capital and labour remunerated at their marginal productivities. Firms, and consequently firm owners, cannot accumulate profits. In financial markets, interest rates are less inflated by profit margins. It becomes evident - following this chain of argument - that the larger the levels of openness to international trade are, then the lower income inequality is (Roine et al., 2009).

Careful analysis of international economics, however, provides an opposite argument as well. Openness to trade may have a positive effect on income inequality basically via increasing skill premia. This argument follows on from the observation that tasks performed by skilled workers naturally generate economies of scale, given that they are associated with costly R&D activities. Since falling barriers to trade ensure access to a larger market, this opens opportunities to benefit from economies of scale in skill-intensive activities. As (skilled) labour productivity increases, firms increase the demand for skilled labour (Manasse and Turrini, 2001; Epifani and Gancia, 2008).

The empirical evidence on the impact of openness to trade on income inequality is ambiguous. White and Anderson (2001), Dollar and Kraay (2002), Higgins and Williamson (1999) and Edwards (1997) find no support for the hypothesis that trade openness is associated with higher income inequality. The last three works, in addition to Calderón and Chong (2001), also test a more specific hypothesis for the developed countries, but again find no evidence to support it. Others, on the other hand, confirm that the effects may be negative (i.e. inequality increasing) when trade takes place horizontally among advanced countries (Lundberg and Squire, 2003; Barro, 2000). The evidence regarding the effects of horizontal international trade confirms the basic intuition that extra profits and quasi-rents play a central role in increasing income inequality. The possible explanation for this is analogous to the skill-premia driven effect: horizontal trade flows free up capacities and allow economies of scale to be taken advantage of. As a consequence, increasing market shares lead to an increase in market power and, finally, higher extra profits in the hands of just a few. The closer the conditions of product and factor markets to competitive equilibrium, the lower the chances that the accumulation of profits may help increase income inequality.

The Kuznets hypothesis finds new support when integrated with the Schumpeterian legacy. According to Schumpeter, technological change is the ultimate cause of economic growth. Hence, the faster the rate of technological change and the rate of economic growth are, then the lower the levels of income inequality should be. The Schumpeterian hypothesis applies to the right side of the Kuznets' inverted U, meaning that it particularly concerns countries and historic times beyond the radical transformation.

3. The hypothesis: rent inequalities in the Schumpeterian legacy

The growth literature so far has shown that the rate of technological change is a key determinant of economic growth. Economic growth does not take place only via the traditional mechanisms that relate savings to capital intensity, labour productivity and wages, but also, and above all, via an increase in the general efficiency of economic activities stemming from the introduction of new technologies. From this viewpoint, through the fast rate that innovations are introduced, technological change magnifies and empowers the negative relationship between economic growth and income inequalities identified by Kuznets. The grafting of the Schumpeterian legacy to this debate yields important results.

So far, the reappraisal of the Schumpeterian legacy has stressed a reduction in income inequalities stemming from the introduction of labour intensive technologies, paying more attention to the direction rather than the rate of technological change (Aghion et al., 2014). This literature has paid much attention to the effects of skill-biased asymmetries caused by technological change on income in terms of wage inequalities as if wages were the main component of income (Helpman, 1997; Aghion and Howitt, 1997). Along these lines, Grossman (2001) provides a comprehensive review of the literature by reporting the income inequality enhancing effects of the skill-biased direction of technological change (Acemoglu, 2002 and 2003; Okazawa, 2013) and stressing the effects on wage inequalities, but paying little attention to analysing the effects of technological change on rents. Specifically, in the context of the skill-bias hypothesis, it has been suggested that the new factor intensity of technological change could be responsible for the increase in wage inequalities observed in the new century. According to this literature, the introduction of new technologies, strongly biased in favour of skilled labour, may have affected labour markets with a sharp increase in the skill premium and a reduction in real wages for low-skilled workers with a major increase in wage asymmetries and hence income asymmetries (Acemoglu, 2002 and 2003; Burstein and Vogel, 2010; Costinot and Vogel, 2010; Vanhoudt, 2000).[3]

This literature has not yet fully taken into consideration the important implications of the Schumpeterian legacy with regard to income inequality that are engendered by the effects of the rate – rather than the direction – of technological change on both wealth and rent inequalities (Aghion et al., 2015a). Schumpeter contributes to the Kuznets' hypothesis by confirming that growth, as determined by technological change, exerts a positive effect on the reduction in income asymmetry. According to Schumpeter, in fact, the introduction of technological innovations is an intrinsic characteristic of the working of economic systems and cannot be separated from economic growth: technological change and economic growth are intertwined. This interdependence has been further clarified by recent advances of the economics of innovation that have brought attention to the contribution of Schumpeter (1934) on the role of entrepreneurship in the introduction of radical innovations (Acs et al., 2013; Aparicio et al., 2016a, 2016b), rather in contrast to the Schumpeterian focus (Schumpeter, 1942) on the innovative potential of large corporations. The importance of entrepreneurship consists in the fact that the positive rate of technological change is more powerful in reducing income inequality when it is the product of newcomers rather than incumbents (Bruton et al., 2013). The appreciation of the role of entrepreneurship as a major determinant of the introduction of innovations leads us to emphasize that the contribution of the rate of technological change to lowering income inequality goes through a reduction in asymmetry in the distribution of wealth through rents. The latter are an important component of income and income inequality is therefore crucially determined by the effects of wealth distribution in terms of rents.

The rate of technological change affects the rent component of income distribution via four distinct mechanisms: A) the destruction of existing capital stock; B) the entry of new firms; C) the reduction in mark-ups and monopolistic rents paid as dividend to shareholders of incumbents; D) the increase in savings with a consequent reduction in the rates of interest paid to bond holders. We will now analyse them in detail.

A) The introduction of both product and process innovations causes creative destruction, with the wipe-out of large portions of the existing capital. Shareholders of incumbents forced to exit the product markets suffer losses that reduce their wealth. The rate of technological change is thus likely to reduce the income asymmetries stemming from an uneven distribution of wealth.
B) Considerable evidence confirms that radical innovations are generated mainly by newcomers rather than by incumbents. Detailed studies show that the emergence of new information and communication technologies and biotechnologies in the second part of the 20th century has been primarily the outcome of entrepreneurship, as in the early Schumpeter (1934), rather than corporations, as in Schumpeter (1942) and Nelson and Winter (1982). Fast rates of technological change are associated with the creation of new firms by new entrepreneurs that are able to challenge the incumbents by means of the introduction of radical innovations. Innovations are in turn associated with upward mobility (Aghion et al., 2015b; Aparicio et al., 2016a, 2016b; SanchisLlopis et al., 2015).
C) The entry of innovators engenders an increase in market rivalry and a reduction in barriers to entry. Hence, it squeezes extra profits and shortens the duration of accumulation of monopolistic rents of incumbents (Aghion et al., 2014). Consequently, the reduction in the levels and duration of monopolistic rents reduces rents in terms of the dividend paid to shareholders of incumbents (the non-wage component of income) and hence income inequality. Entrepreneurs do earn extra profits. However, they are rarely the offspring of wealthy families: rather they come from the middle class. Consequently, the extra profits of newcomers help to create new stocks of wealth that start from scratch, reducing the general levels of wealth inequality (Link and Siegel, 2007).
D) Technological change helps increase total factor productivity and hence labour productivity. The increase in labour productivity has positive effects on wages. Higher levels of labour productivity increase wages, hence the absolute levels of savings and capital supply: interest rates gradually fall. This leads to a more symmetric distribution of income due to a weakening share of income held by bondholders.

The combined effect of the four mechanisms leads us to formulate our main hypothesis: the faster the rate of technological change, the lower the income inequality via its negative effects on rent inequalities. Our hypothesis pays specific attention to the dynamics of the top income levels across countries by emphasizing the comparative analysis.

Since the rate of technological change exerts its effects primarily via creative destruction, it is expected to reduce income inequality by

[3] There are other reasons for an increase in the skill premium. Trade is one of the most widely discussed factors (e.g. Deardoff (2000), Panagariya (2000) and Epifani and Gancia (2008)). Offshoring activities have also been found to explain the rise in the skill premium with the pioneering contributions by Feenstra and Hanson (1997, 1999) documenting this relationship. For a more detailed overview of these and other factors, see Gandolfo (2014).

means of a reduction in wealth inequality, especially when and where it is highly skewed in favour of a small fraction of the population. Moreover, the negative relationship between the rate of technological change and income inequality is expected to have a stronger impact in countries where the income distribution is ex-ante more skewed. Because creative destruction affects the existing stock of capital and its rents, technological change should primarily harm the rich. If wealth is concentrated in a small fraction of the population, the negative effects of the rates of introduction of innovations should be stronger in countries where the upper quantiles of the population commands a larger share of the income because they hold a larger share of the wealth. Consequently, from an international comparative perspective, the effects of the rate of introduction of innovations will be stronger in countries with higher levels of income asymmetry. In countries where income inequality is larger, wealth inequality should also be larger, and hence the effects of the creative destruction engendered by the introduction of innovations should be larger. To verify this hypothesis, quantile regressions are the appropriate econometric tool.

Before testing our hypothesis econometrically, it seems useful to note that, following Gordon (2000 and 2012), the slowdown of technological change experienced since the last decades of the 20th century parallels the reduction in total factor productivity growth and increase in income inequality (Piketty, 2014). This descriptive evidence may be interpreted as a clue that the decline in technological opportunities and reduction in the rate of introduction of technological change are a plausible cause of the increase in income inequality. Table 1 provides evidence on the evolution of the cost of knowledge, as measured by R&D expenses per patent in the years 1985–2010, and of productivity growth. This evidence shows that the unit cost of knowledge, after a sharp reduction in the period 1985–2000, has been increasing thereafter. This seems to confirm the slowdown in technological opportunities since the end of the 20th century. The decline in the rates of increase of total factor productivity seems to confirm a reduction in the rates of introduction of innovations. Both parallel the increase in income asymmetries experienced since the end of the 20th century.

4. Empirical evidence

4.1. Econometric strategy

We test the hypothesis raised in the previous section in an empirical exercise on a panel of 39 countries, over the period 1995–2011. The set of countries is characterized by a controlled variance with respect to the key parameters. The data set includes only countries for which all the relevant data are available so as to avoid the inclusion of an array of cases for which the key variable exhibits trivial figures.[4] The exclusion of developing countries and the reduction of the span of variance to a set of countries able to introduce technological changes is consistent with the basic hypothesis – the Kuznets-Schumpeter line of analysis – according to which economic growth, after the drastic discontinuity of the transition from rural to urban economies, favours a reduction in income asymmetry. This selection of the data set enables the right-hand side of the inverted U-relationship to be tested, i.e. the hypothesis that the faster the rate of technological change and hence economic growth are, then the lower the levels of income asymmetry will be in countries and historic times beyond the radical transformation. The data set includes, in fact, the industrializing countries within the European Union such as Slovakia, Lithuania, Hungary, Latvia, Romania, Bulgaria, Poland, Estonia, Czech Republic and Slovenia and BRIC such as Brazil, Turkey, Russia, India, China and Cyprus alongside the standard groups of advanced countries such as United States, United Kingdom, Canada, Japan, Germany, France, Belgium, Italy, Portugal, the Netherlands, Sweden, Denmark, Malta, Austria, Switzerland, Finland, Sweden, Ireland, Luxemburg and Spain. This data set based on the capability to command the introduction of technological innovations seems a reliable sample for testing the effects of technological change on income distribution.

The previous discussion on the link between inequality and growth suggests that there are numerous conceptual and methodological caveats to be taken into account. First, from a conceptual point of view, it is clear that technological change is endogenous – at least to some extent – to a more general process of economic growth so that the link between inequality and innovation could be signed by two-way causality. This challenges the estimation strategy with obvious simultaneity problems. Consequently, to deal with the issue, we corroborate our baseline results by running the original static regressions with lagged explanatory variables.

Second, applying an adequate measure of technological change is not obvious. Due to the complex nature of technological change, we acknowledge that there is no single indicator that optimally measures it, but that each one has its advantages and limitations. Among possible candidates, R&D expenditure, a typical input measure, has been more and more criticized for its limitations. Recent advances in the literature stress that, next to R&D, many other relevant inputs play a central role in the generation of new technological knowledge and in the eventual introduction of innovation. Total factor productivity - an alternative indicator of the rate of technological change - suffers from many equilibrium assumptions. Its reliability may be limited, especially in a context characterized by long-term development, with major changes in the structure and organization of the underlying economic systems.

Past empirical studies using patent-related indicators often applied some measures to account for differences in the quality of individual patents. For instance, Jaffe et al. (1993) use patent citations, whereas Aghion et al. (2005) refer to citation-weighted patent grants. Since we are interested in flows of newly available knowledge, we consider patent applications as the most suitable measure of technological progress. Moreover, the increasing evidence of the actual meaning of patent citations suggests relying on the sheer number of patents without attempting to use citations as a proxy for their quality. As a matter of fact, it is now clear that citations to other patents are included by patent officers to better specify the borders of the domain of the intellectual property right rather than their quality (Van Zeebroeck, 2011 and Van Zeebroeck and van Pottelsberghe, 2011). In view of such limitations, our choice is to make use of patent counts, a typical measure of the output of the innovative process, which is able to approximate well the generation of technological knowledge *actually* dedicated to economic applications.

This is a flow measure that directly reflects the increase in the stock of technological knowledge available in an economic system.[5] Accordingly, patents have been extensively used in the management and economics literature to measure knowledge flows (e.g., Griliches, 1990; Jaffe et al., 1993 and 1998; Almeida and Kogut, 1999; Popp, 2003 and 2005; Alcacer and Gittelman, 2006). As such, patent data are potentially more precise than other measures of innovation since they refer to concrete and successfully terminated knowledge generating activities that are the result of the recombination of codified knowledge based on research and development efforts and the stock of tacit knowledge based upon learning processes.

Third, we bear in mind the many issues - and limitations - connected with the measurement of income inequality. Following Aghion et al.

[4] Important countries such as South Korea, South Africa and Argentina could not be included due to the lack of a full set of variables.

[5] We recall the relevant literature that deals with the respective advantages and drawbacks connected with the use of patent data to measure productivity (see, for instance, Griliches, 1990; Napolitano and Sirilli, 1990; Popp, 2005). Nevertheless, in our context, where we are particularly interested in the distribution of income, the count of patents seems to measure remunerable technological change more reliably than some measures of factor productivity, be it the growth of total factor productivity or labour productivity.

(1999), we use the Eurostat definition of income, i.e. the total disposable income of a household.[6] This is calculated by summing up the personal income gained by each member of a household and non-labour income received at the household level. In this way, disposable income includes: income from work (wages of employed persons and earnings of the self-employed), private income from investment and property, transfers between households, all social transfers received in cash (including old-age pensions). We measure income inequality with the Gini coefficient, quintiles of income distribution and ratios between them.

Finally, there are reasons for preferring multi-year averaged data to annual observations. First, given that some of our variables are expressed in terms of growth rates, they are relatively noisy at annual frequency. Second, by averaging the annual observations, we avoid the possible influence of the business cycle. Third, the estimations based on multi-year averages are more adequate for offering medium-term conclusions in the investigation of the underlying hypothesis. Consequently, to study our main specifications, we transform our annual data into 4-year averages.[7]

Bearing in mind the considerations outlined in the previous section, the implications of our conceptual design for the empirical investigation could be very different if the *mean* inequality reduction were uneven along the distribution of the Gini coefficient.

Indeed, application of mean linear estimation methods implies that with respect to each point on the conditional distribution, the estimates of the relationship between inequality and the explanatory variables remain the same. This assumption may be restrictive and to test the relative importance of the factors determining income inequality at different points of the conditional distribution, it is appropriate to apply quantile regression. Nonetheless, we did mean linear estimations as well. For the pooled OLS as well as when applying feasible GLS methods, the estimation results performed reasonably well. We could not conclude the same for the fixed effects (FE) estimations.[8] This is due to the fact that the cross-sectional variability of our main variables in our sample is high with respect to the within variation. Instead, the fixed effects model uses only the within variation and eliminates the between variation. As a consequence, after eliminating the cross-sectional variation at the mean of the FE estimations, no reasonable results can be obtained. Appendix A reports the results from different mean linear estimations.

The general form of the regression model for the θ^{th} quantile with $0 \le \theta \le 1$, as first introduced by Koenker and Bassett (1978), can be written as:

$$Q_\theta(y_{it}|\mathbf{X}_{it}) = \mathbf{X}'_{it}\boldsymbol{\beta}_\theta \tag{1}$$

where y_{it} is the dependent variable (Gini coefficient) in country i at time t. Vector $\mathbf{X}_{it}'$ contains the set of explanatory variables as listed and explained below and $\boldsymbol{\beta}_\theta$ is the vector of the regression coefficients to be estimated. Regression coefficients for different quantiles can be directly compared to each other.

The dependent variable (*Ineq*) is an indicator of income inequality which in our baseline case is given by the Gini coefficient.[9] Regarding our explanatory variables, one of the main two factors is *Tech* and stands for the introduction of innovation which we proxy with the count of patent applications. Based on our arguments regarding technological change, we would expect that if the *Tech* variable exerts a positive impact on income distribution, we should see a negative estimation coefficient.

Other controls include: *open* which measures trade openness, *GDPcap* which stands for GDP per capita, *gov* which measures government spending - both as a percentage of GDP - and *FI* which is an indicator of international financial integration. Such variables are commonly referred to when investigating the determinants of wage inequality (for a more detailed discussion, see Roine et al. (2009)).[10] More precisely, as discussed in Section 2, the impact of trade openness on inequality may be both positive and negative, depending on the forces at work. If intensified trade reduces barriers in domestic markets and generates favourable conditions for the operating of more workable competition, more equal income distribution should follow (Roine et al., 2009). If, on the other hand, trade openness enhances the expansion of productive scale, with the positive impact on either demand for skilled labour, or rent extraction, or both, income inequality (also via increasing skill premia) may increase. Which effect prevails is an empirical question. Regarding GDP per capita, since our sample is dominated by countries in advanced stages of development, we could expect the stage of economic development to have an inequality reducing effect. Indeed, in line with our previous discussion, improvements in GDP per capita – possible thanks to the increase in the general level of wages – could enhance income distribution in general. Moreover, as GDP per capita can be seen as measuring the stage of development, the latter may go hand in hand with the adoption of redistributive instruments. Nevertheless, the opposite outcome cannot be excluded, depending on the pro-egalitarian preferences of a society (Guillaud, 2013). Government spending is aimed at capturing the contribution of social policy to a reduction in income inequality. The impact of financial integration on inequality is unsure.[11] If financial markets work imperfectly, favouring the inefficient allocation of financial capital, the beneficial effects of a reduction in interest rates will not occur and the negative consequences on income distribution will be magnified. The opposite is to be expected, if financial market imperfections are substantial.

Fig. B1 in Appendix B gives a first impression of the influence of single explanatory variables on mean income inequality. Whereas the relationship seems to work at the unconditional mean, the precise impact of such factors along the conditional distribution should be clarified in an empirical exercise.

4.2. Data description

The Gini coefficient is taken from Eurostat and for countries not covered by Eurostat, we use the World Bank Development Indicators database. Gini coefficient is defined as the relationship of cumulative shares of the population segregated according to the level of equalized disposable income to the cumulative share of the equalized total disposable income. If the coefficient is equal to zero, this means there is a perfectly equal income distribution, whereas a Gini coefficient of one indicates maximum inequality between the individual incomes. According to the Eurostat definition, the total disposable income of a household is calculated by summing up the personal income gained by each member of a household and non-labour income received at the household level. In this way, disposable income includes: income from work (wages of employed persons and earnings of the self-employed), private income

[6] In his recent book, Thomas Piketty raises concerns regarding the indicators of income inequality usually used in the applied work (Gini coefficient, quantile ratios) mainly because they mask some part of the evolution taking place within the economy (for instance, at the very top of the distribution). This notwithstanding, as a first step in the investigation at stake, we believe there is scope for examining how technological change impacts the distribution of income in a society as a whole, across all classes of income.

[7] There is no consensus regarding the use of 4-, 5-year or other frequency of averages. Quite often 5-year averages have been investigated, but without providing a clear motivation for the choice. We opt for 4-year averages to maximize the number of observations per country. Our database ranges between 1995 and 2011, but to obtain our 4-year averages, we exclude 1995 which reported many missing values.

[8] A similar performance of the pooled versus FE mean estimations was documented in Ohinata and van Ours (2012) when studying spillover effects of immigrants on the performance of students. Consequently, their main methodological choice was quantile regression.

[9] On the origins of the Gini coefficient, see Ceriani and Verme (2012).

[10] Additionally, in separate estimations not reported here, we included the square of GDP per capita – as a common way of testing the standard Kuznets hypothesis – but it was always insignificant, in line with the mixed empirical evidence of a dedicated strand of the literature (Jha, 1996; Mushinsky, 2001).

[11] The ongoing discussion in the literature concerning the growth and welfare effects of progressing financial globalization is far from conclusive. For a comprehensive review on the issue, see Kose et al. (2009).

from investment and property, transfers between households, all social transfers received in cash (including old-age pensions).

In the sensitivity analysis, other measures of income inequality expressed as quantiles of income distribution are used instead of the Gini index. More precisely, we consider the ratio between the fifth and the first quantile of income distribution. However, the data reliability is limited here, due to a number of missing observations.

The patent variable refers to the ratio between the number of patent applications made each year directly to WIPO and national phase entries and GDP at constant U.S. dollars prices. In this way, we weight the absolute number of patents by the size of the economy.

The Penn World Tables are the source used for our measure of trade openness (*openk*) and government spending in percentage to GDP (*kg*). From World Economic Outlook we take GDP per capita (expressed in millions of PPP current international dollars).

Finally, as a measure of financial integration, we apply a *de jure* indicator taken from an updated database developed by Chinn and Ito (2008).[12] This indicator is obtained in an estimation procedure, based on a principal components model. The authors use the data from the Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER) by the International Monetary Fund (IMF). In the construction of the index, information is used on the presence (or absence) of multiple exchange rates, on restrictions on current account and capital account transactions, and on the requirement of the surrender of export proceeds. This index covers all the countries and years included in our sample.

Descriptive statistics of the variables are included in Table C1 of Appendix C.

4.3. Results

Table 2 summarizes the main results of the quantile regressions. Generally, the results confirm the evidence of a strong inequality-reducing effect of technological change.[13] This result is, however, insignificant (or at best only weakly significant) in the first three quantiles. This implies that the inequality reducing effects of the rate of technological change start to operate only at a certain level of income inequality and increase with the levels of income inequality.[14] The econometric results change considerably with the deciles of the Gini concentration: the estimated parameter of *Tech* is 0.032 and is insignificant for Q10, 0.042 at a 5% significance levels for Q40, and 0.094 at a 1% significance levels for Q90. These results show that the effects of the rate of technological change, both in terms of the estimated value of the parameter and its statistical reliability, are stronger, the stronger the levels of income inequality are. This in turn may be considered a strong clue to the strength of the relationship between the rate of technological change and the rent component of disposable income. High levels of income inequality, in fact, reflect high levels of wealth inequality.

In general, our evidence suggests that a one unit increase in patent share over GDP provokes a reduction in income inequality of around 7 to 10%. Since the patent share grew in the observed sample at an average yearly rate of 0.2%, income inequality due to innovation was reduced by 1.4%.

Regarding the other control variables, all of them, with the remarkable exception of the index of financial integration, contributed to the reduction in income inequality. In particular, for trade openness, we report negative estimation coefficients for all quantiles of income distribution, with the strongest effect in the first three quantiles. This suggests that intensifying trade relations played a role in reducing income disparities and, moreover, that at lower levels of income inequality the magnitude of the effect was greater. Finally, based on the composition of our sample, our findings should be only limitedly comparable with the outcomes of past investigations. Consequently, the result should be interpreted in relation to the specific country composition and less as a support for any particular outcome from the past empirical literature.

The negative coefficient found for GDP per capita strictly relates to our conceptual design previously discussed. Indeed, the increase in GDP per capita, implicitly stemming from an increase in wages, leads to a reduction in income inequalities. Finally, the result regarding financial liberalization is in line with the outcomes obtained by Rajan and Zingales (2003) and by Ang (2010), the last investigating the case of India in a co-integration framework.

4.4. Sensitivity analysis

4.4.1. Estimations on lagged explanatory variables

We are mindful of the potential endogeneity concerns when analysing the relationship between income inequality and technological change. Indeed, the level of inequality may be influential on the country's ability to promote technological improvements.

As our robustness check in this regard, we lagged the explanatory variables by one period to verify whether our main results are still valid. It has to be noted, however, that by lagging we lose some information so that these results are not directly comparable with the ones from the baseline model. Nonetheless, they show whether the direction of influence remains consistent with the estimations with contemporaneous observations.

Table 3 summarizes the estimated results which corroborate our previous conclusions: income inequality diminishes at higher rates of technological change. The strong relationship between the rates of technological change and the quantiles exhibits again increasing effects that are stronger at higher quantiles of income inequality.

4.4.2. Direction of technological change and the skill content

Our primary scope is to assess the overall impact of the rate of technological change on income inequality. This notwithstanding, with the aim of better linking our contribution to the previous literature on the inequality consequences of skill-biased technological change, we verify here how the direction and the skills-intensity of technological change may have worked out their influence in the context of our sample. In line with the conceptual developments made in the established literature (Solow, 1957; Antonelli and Quatraro, 2014), we apply the Euler's law to represent the direction of technological change in terms of the share of labour over total output produced in an economy. Indeed, as capital use in production increases due to new capital-intensive technologies, the share of labour over output decreases. Nevertheless, this measure does not necessarily account for the skills content of technological change. We therefore introduce a variable that measures the relative skills intensity in an economy (*human*), measured in terms of the percentage share of the population with the tertiary educational attainment (taken from Eurostat). Additionally, since we presume that the direction of technological change possibly works together with the intensity of skills in an economy, we generate an interaction term between the two variables (*labshare* $*$ *human*). We expect the tests to confirm that the direction of technological change experienced in the last decades increases income inequality via the wage-inequality effects of the skill bias. Moreover, we expect the interaction term (*labshare* $*$ *human*) to capture the effects of the distribution of skills exhibiting a negative sign. The rationale should be clear. For given levels of labour intensity of the new technology, the larger the share of

[12] There are numerous measures of financial liberalization. Due to the date availability issue, we use a *de jure* indicator. Lane and Milesi-Ferretti (2007) develop a broadly used measure of de facto financial liberalization that, however, ends in 2004 and does not therefore cover several years in our observation sample. For a discussion on the advantages and drawbacks of using a *de jure* and non de facto measure of financial integration, see Kose et al. (2009) and Gehringer (2013 and 2015).

[13] The inequality reducing effect of technological change is also confirmed in estimations excluding control variables. We report these results in Table B1 in Appendix B.

[14] This is in line with the findings of Archibugi and Pietrobelli (2003) who find that the globalization of technology has a positive impact on developing countries provided that adequate policies in support of adoption of innovation are introduced.

Table 2
Results from estimations of determinants of income inequality based on baseline specification and using quantile regressions.

	Dependent variable: Gini coefficient								
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Tech	−0.032	−0.047*	−0.040	−0.042**	−0.055**	−0.060***	−0.077***	−0.076***	−0.094***
	(0.024)	(0.026)	(0.026)	(0.018)	(0.018)	(0.018)	(0.018)	(0.024)	(0.024)
open	−0.085***	−0.087***	−0.066**	−0.080***	−0.071***	−0.062***	−0.063***	−0.056***	−0.055***
	(0.017)	(0.020)	(0.021)	(0.018)	(0.013)	(0.013)	(0.013)	(0.014)	(0.013)
GDPcap	−0.013*	−0.015**	−0.016**	−0.021**	−0.019**	−0.019**	−0.015**	−0.010*	−0.015**
	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)	(0.007)	(0.007)	(0.006)	(0.007)
gov	−0.300***	−0.256***	−0.259***	−0.394***	−0.406***	−0.427***	−0.449***	−0.438***	−0.425***
	(0.075)	(0.072)	(0.069)	(0.068)	(0.053)	(0.052)	(0.051)	(0.057)	(0.096)
FI	1.465**	0.761	0.520	0.759*	0.737**	0.456	0.228	−0.485	−4.568**
	(0.602)	(0.702)	(0.587)	(0.388)	(0.342)	(0.461)	(0.728)	(1.264)	(2.149)
N. obs.	130	130	130	130	130	130	130	130	130
Pseudo R-sq.	0.327	0.312	0.335	0.370	0.397	0.409	0.408	0.413	0.451

Note: Dependent variable is the Gini index taken from the Eurostat. *Tech* measures the rate of technological change and is expressed as a ratio between the count of patent applications at WIPO and GDP at constant U.S. dollar prices (from OECD STAN). *Open* is a measure of trade openness and is taken from Penn World Tables. It is given by a share of total trade by a country (imports and exports) over the country's GDP. *GDPcap* is GDP per capita in millions of PPP current international dollars and is taken from the World Economic Outlook. *Gov* is a measure of government spending as a percentage of GDP, as defined by Penn World Tables. Finally, *FI* refers to an indicator of financial integration, as defined by Chinn and Ito (2008). All variables are 4-year averaged over the time span 1996–2011. ***, ** and * indicate significance level at 1%, 5% and 10%, respectively. Bootstrapped standard errors are in parenthesis.

Table 3
Quantile regressions of baseline model with lagged determinants of income inequality.

	Dependent variable: Gini coefficient at time t								
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
$Tech_{t-1}$	−0.021	−0.027	−0.025	−0.023	−0.047**	−0.055**	−0.050**	−0.052**	−0.060**
	(0.021)	(0.020)	(0.020)	(0.021)	(0.022)	(0.020)	(0.020)	(0.020)	(0.027)
$open_{t-1}$	−0.097***	−0.064**	−0.060**	−0.062**	−0.064***	−0.061***	−0.069***	−0.067***	−0.067***
	(0.030)	(0.030)	(0.025)	(0.023)	(0.020)	(0.018)	(0.017)	(0.015)	(0.010)
$GDPcap_{t-1}$	−0.271***	−0.166**	−0.179**	−0.181**	−0.183**	−0.157**	−0.132**	−0.143**	−0.103**
	(0.083)	(0.083)	(0.080)	(0.071)	(0.069)	(0.074)	(0.058)	(0.056)	(0.050)
gov_{t-1}	−0.199**	−0.424***	−0.394***	−0.373***	−0.339***	−0.382***	−0.431***	−0.436***	−0.390***
	(0.095)	(0.069)	(0.055)	(0.064)	(0.069)	(0.067)	(0.069)	(0.064)	(0.069)
FI_{t-1}	1.535**	1.464**	1.404**	1.025	0.892	0.325	0.191	0.084	−4.935**
	(0.779)	(0.640)	(0.517)	(0.638)	(0.587)	(0.436)	(0.412)	(1.183)	(2.315)
N. obs.	96	96	96	96	96	96	96	96	96
Pseudo R-sq.	0.336	0.347	0.401	0.433	0.451	0.455	0.463	0.460	0.489

Note: Dependent variable is the Gini index. For a definition of the explanatory variables, see note to Table 2. All variables are 4-year averaged over the time span 1996–2011. ***, ** and * indicate significance level at 1%, 5% and 10%, respectively. Bootstrapped standard errors are in parenthesis.

population with a formal degree, the lower the wage-inequality increasing effects should be. This reasoning is clearly confirmed in our estimation results (Table 4).

4.4.3. Estimations on different quantiles of income inequality distribution

Our previous estimations regard quantiles that are evenly spread along the income inequality distribution. Now we want to check how previous results are affected if we take a different set of quantiles, namely, Q1, Q25, Q50, Q75 and Q99. The results are summarized in Table 5 below. In particular, in panel *a)* we report the results for specifications analogous to the ones included in Table 2, whereas in panel *b)* we additionally include the human capital variable (*human*) as well as the interaction term between the latter and the labour share variable (*labshare* ∗ *human*). The results in both panels broadly confirm the previous results with the rate of technological change exercising an inequality reducing impact and the skill-biased direction of technological change working against the inequality reduction.

4.4.4. Alternative measures of income inequality

As our main measure of income inequality we adopt the Gini index that is the most commonly used and most available inequality index. Nevertheless, there are numerous other possible measures that have been identified in the past literature and used in empirical investigations.[15] One alternative is given by considering quantile shares or ratios between different quantiles of within country income distribution. For instance, in addition to the Gini index, Panizza (2002) applies the share of the third quintile (Q3) of the income distribution, whereas Xu and Zou (2000) study the fifth (Q5), the first (Q1), the third and fourth together (Q34), and the ratio between the fifth and the first (Q5/Q1) quintile. All are supposed to express the changing proportions of the overall income distribution of the rich (Q5), the poor (Q1), the middle class (Q34) and the relative share relating to the two extreme classes (Q5/Q1). Apart from the practical reasons of worse data availability, an important drawback of such quintile (or also percentile) measures of income inequality is that they ignore a piece of information concerning the shares of distribution other than those selected. The Gini index, on the contrary, summarizes the information over the entire income distribution. This notwithstanding, and bearing in mind the underlying limitations, we apply three alternative quintile-based measures of income inequality, namely, Q5 and the two ratios, Q5/Q1 and Q5/Q3. As the results were comparable between the three measures, we report the results regarding the ratio Q5/Q1.

[15] For a comprehensive review of different methods to measure inequality, see Jenkins and Van Kerm (2006).

Table 4
Quantile regressions of determinants of income inequality with a test of role of skill-biased direction of technological change.

	Dependent variable: Gini coefficient								
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Tech	−0.034	−0.046	−0.054**	−0.061***	−0.076***	−0.075**	−0.088**	−0.082**	−0.099**
	(0.035)	(0.033)	(0.025)	(0.023)	(0.026)	(0.030)	(0.039)	(0.040)	(0.046)
labshare	0.476*	0.641***	0.798***	0.745***	0.769***	0.640**	0.608**	0.718**	1.040***
	(0.280)	(0.232)	(0.205)	(0.198)	(0.246)	(0.245)	(0.260)	(0.290)	(0.249)
human	2.080**	2.360***	2.320***	2.360***	2.690***	2.390**	2.540**	2.770**	3.650***
	(1.001)	(0.822)	(0.825)	(0.743)	(0.946)	(0.918)	(1.020)	(1.190)	(1.130)
labshare ∗ human	−0.036**	−0.042***	−0.042***	−0.044***	−0.049***	−0.043**	−0.045**	−0.049**	−0.068***
	(0.018)	(0.014)	(0.015)	(0.013)	(0.017)	(0.017)	(0.019)	(0.022)	(0.021)
open	−0.106***	−0.092***	−0.071***	−0.068***	−0.066***	−0.062***	−0.058***	−0.064***	−0.054***
	(0.021)	(0.020)	(0.021)	(0.021)	(0.017)	(0.014)	(0.013)	(0.013)	(0.014)
GDPcap	−0.031***	−0.020**	−0.024***	−0.019***	−0.019***	−0.013**	−0.012*	−0.012*	−0.015**
	(0.008)	(0.009)	(0.007)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)
gov	−0.194	−0.337**	−0.434***	−0.399***	−0.347***	−0.388***	−0.368***	−0.302***	−0.206**
	(0.144)	(0.132)	(0.100)	(0.082)	(0.064)	(0.052)	(0.071)	(0.082)	(0.099)
FI	0.826	0.668	0.858	1.010**	1.280***	0.814**	0.893**	1.080**	0.711
	(0.567)	(0.629)	(0.525)	(0.489)	−0.362	(0.343)	(0.431)	(0.533)	(0.607)
N. obs.	100	100	100	100	100	100	100	100	100
Pseudo R-sq.	0.385	0.349	0.394	0.437	0.455	0.475	0.482	0.480	0.492

Note: Dependent variable is the Gini index. *Labshare* is the share of labour over the output produced in the economy. *Human* is the share of population with a tertiary educational degree. Both variables are constructed based on statistical information taken from the Eurostat. For a definition of the other explanatory variables, see note to Table 2. All variables are 4-year averaged over the time span 1996–2011. ***, ** and * indicate significance level at 1%, 5% and 10%, respectively. Bootstrapped standard errors are in parenthesis.

The results of our estimations, summarized in Tables 6a and 6b, confirm those obtained previously regarding the technological variables (although the estimated effects are never significant at 1% level) and also the other controls. The only difference, though remarkable, regards the testing for the direction of technological change. In particular, both when considered in terms of the labour share over income (Table 6a) and when accounting for the actual skills-intensity (Table 6b), the effect of the direction of technological change remained insignificant, although the estimated coefficients show the expected signs. This difference in the results between the adoption of the Gini coefficient

Table 5
Quantile based on alternative definition of quintiles.

	Q01	Q25	Q50	Q75	Q99
a)					
Tech	−0.075**	−0.022	−0.055***	−0.070***	−0.145**
	(0.031)	(0.026)	(0.016)	(0.020)	(0.047)
open	−0.097***	−0.084***	−0.071***	−0.052***	−0.047**
	(0.017)	(0.019)	(0.015)	(0.013)	(0.016)
GDPcap	−0.027***	−0.014*	−0.018**	−0.012*	−0.011
	(0.001)	(0.007)	(0.001)	(0.001)	(0.001)
gov	−0.159*	−0.295***	−0.406***	−0.418***	−0.407***
	(0.093)	(0.084)	(0.049)	(0.055)	(0.101)
FI	2.457***	0.600	0.737	−0.456	−5.138**
	(0.697)	(0.608)	(0.482)	(1.099)	(1.887)
N. obs.	130	130	130	130	130
Pseudo R-sq.	0.374	0.319	0.397	0.411	0.690
b)					
Tech	−0.045	−0.053*	−0.076***	−0.070**	−0.153***
	(0.036)	(0.031)	(0.021)	(0.034)	(0.047)
labshare	0.569	0.704**	0.769***	0.861***	1.050**
	(0.364)	(0.315)	(0.220)	(0.309)	(0.406)
human	1.280	2.100**	2.690***	3.290**	4.180**
	(1.100)	(1.050)	(0.990)	(1.350)	(1.600)
labshare ∗ human	−0.023	−0.038**	−0.049***	−0.060**	−0.076**
	(0.020)	(0.018)	(0.018)	(0.025)	(0.030)
open	−0.107***	−0.076***	−0.066***	−0.063***	−0.064***
	(0.022)	(0.024)	(0.017)	(0.013)	(0.014)
GDPcap	−0.029***	−0.025**	−0.019***	−0.014**	−0.015**
	(0.010)	(0.010)	(0.006)	(0.006)	(0.007)
gov	−0.282*	−0.415***	−0.347***	−0.324***	−0.191
	(0.163)	(0.120)	(0.082)	(0.095)	(0.121)
FI	0.492	1.140**	1.280***	1.020***	0.991
	(0.602)	(0.513)	(0.356)	(0.384)	(0.719)
N. obs.	100	100	100	100	100
Pseudo R-sq.	0.485	0.367	0.455	0.477	0.672

Note: Dependent variable is the Gini index. For a definition of the explanatory variables, see note to Tables 2 and 4. All variables are 4-year averaged over the time span 1996–2011. ***, ** and * indicate significance level at 1%, 5% and 10%, respectively. Bootstrapped standard errors are in parenthesis.

Table 6a
Quantile regressions of determinants of income inequality based on alternative measure of income inequality.

	Dependent variable: ratio between Q5 and Q1 of the (within country) income distribution								
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Tech	−0.011*	−0.013*	−0.017**	−0.013	−0.012	−0.016**	−0.017**	−0.022***	−0.018**
	(0.006)	(0.007)	(0.008)	(0.008)	(0.007)	(0.007)	(0.008)	(0.006)	(0.008)
open	−0.020***	−0.020***	−0.018***	−0.018***	−0.016***	−0.015***	−0.012**	−0.009**	−0.011**
	(0.005)	(0.006)	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
GDPcap	−0.059**	−0.076***	−0.066***	−0.064***	−0.067***	−0.068**	−0.054**	−0.067**	−0.066**
	(0.029)	(0.021)	(0.016)	(0.019)	(0.020)	(0.022)	(0.024)	(0.027)	(0.025)
gov	−0.050*	−0.053**	−0.069**	−0.083**	−0.092***	−0.095***	−0.083***	−0.074***	−0.065**
	(0.027)	(0.023)	(0.023)	(0.026)	(0.024)	(0.022)	(0.024)	(0.020)	(0.024)
FI	0.160	0.363*	0.089	0.044	−0.003	−0.081	−0.570	−1.047	−5.800**
	(0.293)	(0.193)	(0.181)	(0.153)	(0.211)	(0.846)	(1.377)	(2.352)	(2.326)
N. obs.	97	97	97	97	97	97	97	97	97
Pseudo R-sq.	0.171	0.220	0.265	0.307	0.331	0.336	0.327	0.330	0.575

Note: Dependent variable is given by the ratio between the fifth and first quintile (Q5/Q1). For a definition of the explanatory variables, see note to Table 2. All variables are 4-year non-overlapping averages over the period 1996–2011. ***, ** and * indicate significance level at 1%, 5% and 10%, respectively. Bootstrapped standard errors are in parenthesis.

versus the ratio Q5/Q1 may have two origins. First, it may be due to the different informational contents of the two indicators as explained before. Second, there is a difference in the data availability: it was better for the Gini coefficient than for the single quintiles.

Once more we note that the effects of the rate of introduction of technological changes increase with the levels of income inequality as identified by the quantiles considered. The effects are negligible in countries where the income inequality is low, but increase both in terms of statistical significance and size of the estimated parameter in countries with higher levels of income inequality.

5. Conclusion

Increasing levels of income inequality are attracting much research. The literature has concentrated on the hypothesis that increasing levels of income inequality are the cause of slow growth and social unbalances. This paper contributes to exploring an alternative hypothesis according to which increasing levels of income inequality are the consequence, rather than the cause, of slow growth and, more specifically, of the slowing pace of technological change. Indeed, very little investigation has been made into the role of the rate of technological change – as distinct from its direction – as a crucial component of the dynamics of income distribution associated with economic growth.

Building on a more comprehensive reappraisal of the Schumpeterian legacy in our analysis that appreciates the role of entrepreneurship in assessing the rates of introduction of technological innovations, we demonstrate that the rate of technological change – as measured by the flow of patents – and the consequent effects of the creative destruction on the distribution of wealth and their rents plays a crucial role in reducing income asymmetries. Slow rates of technological change help to consolidate barriers to entry and limit the working of price competition. The transfer of increased efficiency to the final consumer is substantially delayed. The owners of wealth can take advantage of enduring high-level monopolistic rents. When, on the other hand, the rate of technological change is high, with the frequent introduction of innovations stirred by market rivalry among competitors, the successive waves of creative destruction reduce barriers to entry and trim the duration of transient monopolistic rents. In this way, technological change

Table 6b
Quantile regressions of determinants of income inequality based on an alternative measure of income inequality and verifying role of skilled-biased direction of technological change.

	Dependent variable: ratio between Q5 and Q1 of the (within country) income distribution								
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Tech	−0.016	−0.010	−0.013	−0.018**	−0.020**	−0.023*	−0.021*	−0.018	−0.022**
	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)	(0.012)	(0.012)	(0.013)	(0.010)
labshare	0.058	0.023	0.041	0.020	0.049	0.058	0.070	0.057	0.036
	(0.058)	(0.074)	(0.071)	(0.076)	(0.065)	(0.061)	(0.064)	(0.068)	(0.090)
human	0.147	−0.129	−0.049	−0.041	0.131	0.170	0.297	0.223	0.169
	(0.278)	(0.269)	(0.268)	(0.312)	(0.294)	(0.275)	(0.261)	(0.273)	(0.342)
labshare ∗ *human*	−0.003	0.002	0.001	0.001	−0.003	−0.003	−0.005	−0.004	−0.003
	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)
open	−0.012**	−0.023***	−0.021***	−0.016***	−0.011*	−0.0127**	−0.011**	−0.008	−0.006
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)
GDPcap	−0.060***	−0.067***	−0.081***	−0.079***	−0.064***	−0.049**	−0.059***	−0.086***	−0.088***
	(0.018)	(0.024)	(0.024)	(0.024)	(0.019)	(0.019)	(0.019)	(0.021)	(0.019)
gov	−0.080***	−0.093**	−0.086***	−0.061**	−0.078***	−0.082***	−0.086***	−0.082***	−0.071***
	(0.023)	(0.035)	(0.031)	(0.025)	(0.023)	(0.024)	(0.025)	(0.023)	(0.022)
FI	0.094	0.216	0.421	0.437	0.469	0.149	0.305	−0.849	−0.873
	(0.544)	(0.305)	(0.321)	(0.279)	(0.332)	(0.561)	(0.626)	(0.644)	(0.654)
N. obs.	74	74	74	74	74	74	74	74	74
Pseudo R-sq.	0.324	0.336	0.371	0.440	0.484	0.513	0.527	0.549	0.639

Note: Dependent variable is given by the ratio between the fifth and first quintile (Q5/Q1). For a definition of the explanatory variables, see note to Tables 2 and 4. All variables are 4-year non-overlapping averages over the period 1996–2011. ***, ** and * indicate significance level at 1%, 5% and 10%, respectively. Bootstrapped standard errors are in parenthesis.

has the chance of deploying all its income-inequality reducing effects via a reduction in rents. Specifically, the introduction of innovations trims rents for three reasons. First, the old vintages of installed capital are destroyed and their owners incur substantial reductions in their wealth. Second, the extra profits stemming from the introduction of innovation are quickly eroded by the following mechanisms: the reduction in monopolistic rents limits the asymmetric income advantages of wealth owners, i.e. shareholders; the levels of profit decline together with its distribution through dividends to shareholders; finally, fast technological change enhances productivity. The benefits of an increase in productivity are quickly transferred to the final consumer with positive effects on savings and the supply of capital. This, in turn, leads to a decline in interest rates paid to bondholders with a further reduction in rent asymmetries.

The results of our comparative econometric test on a large and coherent international sample of countries able to command the introduction of technological change fully confirm the Schumpeterian hypothesis that the faster the rate of introduction of innovation, the lower the levels of income inequality. Moreover, the results of the quantile regressions show that the effects of the rate of introduction of technological change are stronger, the higher the levels of income inequality. This, in turn, seems to support the strong relationship between the rate of technological change and the rent component of disposable income. High levels of income inequality, in fact, reflect high levels of wealth inequality. Top income levels are most affected by the rates of introduction of innovations because of their strong equalizing effects on the distribution of the stocks of wealth and related rents. The Schumpeterian creative destruction displays its effects all the more in countries where income distribution is more skewed towards the wealthy because it primarily affects the wealth of incumbents and, consequently, mainly reduces the top incomes based on rents.

In a sensitivity check, we were also able to confirm the hypothesis that the recent trends of technological change directed towards the use of skilled manpower with formal training contributes to an increase in income inequality via wage inequality, especially when and where the low levels of human capital enable small groups of talented workers to appropriate large shares of revenue. These results confirm that our hypothesis regarding the negative effects of the rate of introduction of technological change on rent and consequently income inequality complements the results of the literature that has explored the effects of the direction of technological change on wage and hence income inequalities. The two hypotheses complement each other in providing a comprehensive reappraisal of the Schumpeterian legacy.

Policy implications are quite important. Innovation policies that are able to support the rates of introduction of innovations, together with competition policies, are the most effective tools for reducing income inequality. Innovation policies aimed at fostering the rate of introduction of technological changes are one of the most effective tools for reducing income inequalities. Competition policy can play a central role in reducing income inequality stemming from rents, especially in product markets where price competition is limited by barriers to entry and to imitation, based on exclusive cost advantages that draw their origin from previous technological vintages. From this viewpoint, innovation and competition policies are complementary.

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Appendix A

Our main estimation framework is based on quantile regressions to account for the fact that the influence of the explanatory variables on the dependent variable may be different along its distribution. Nevertheless, it may be interesting to compare these results with the effects at the mean of income inequality distribution. For this reason, we re-estimate our basic regression with three different methods, namely, Pooled OLS, FGLS and FE. Table A1 reports the results. In the first three columns of the table we exclude the trend variable. The last two columns, on the other hand, show the results of FGLS and FE estimations of specifications including the time trend. The reason behind this estimation is to verify whether inequality may follow some common historical trend, rather than be influenced by technological change. The insignificance of the time trend suggests that the recent developments in income inequality are indeed driven by factors considered in our estimation framework.

Table A1
Estimation results at the mean of the income inequality distribution.

	Pooled OLS	FGLS	FE	FGLS	FE
Tech	−0.066***	−0.068***	−0.043	−0.068***	−0.043
	(0.020)	(0.024)	(0.041)	(0.024)	(0.041)
open	−0.054***	−0.056***	−0.035	−0.056***	−0.035
	(0.010)	(0.012)	(0.023)	(0.010)	(0.023)
GDPcap	−0.217***	−0.193***	−0.076	−0.193***	−0.076
	(0.043)	(0.043)	(0.143)	(0.043)	(0.143)
gov	−0.390***	−0.323***	−0.074	−0.323***	−0.074
	(0.053)	(0.059)	(0.070)	(0.059)	(0.070)
labshare	0.180**	0.138*	0.105	0.138*	0.105
	(0.075)	(0.071)	(0.099)	(0.071)	(0.099)
human	−0.006	−0.023	−0.032	−0.023	−0.032
	(0.064)	(0.065)	(0.085)	(0.065)	(0.085)
FI	0.760**	0.498	−0.196	0.498	−0.196
	(0.335)	(0.315)	(0.340)	(0.315)	(0.340)
time trend	–	–	–	0.710	0.792
				(0.600)	(0.685)
N. obs.	100	100	100	100	100
R-squared	0.643		0.484		0.478
Wald p-value		0.000		0.000	

Note: Dependent variable is Gini index. For a definition of the explanatory variables, see note to Tables 2 and 4. All variables are 4-year averaged over the time span 1996–2011. ***, ** and * indicate significance level at 1%, 5% and 10%, respectively. For the pooled OLS and FE regressions, robust standard errors are in parenthesis. In the FGLS estimations, we allow for country-specific serial correlation and heteroskedasticity in residuals.

Appendix B

Figure B1 shows simple scatter plots of the main explanatory variable, measuring the rate of technological change, of the labour share over income (x-axis) and the mean income inequality (y-axis) in our sample. Both plots suggest the right sign of the influence as explained in our theoretical discussion: whereas the rate of technological change diminishes income inequality, the skill-biased direction seems to worsen income distribution. The relationship seems thus to work at the unconditional mean, as also confirmed in the results of estimations in Table B1 below. Nevertheless, what the precise impact of technological change on income inequality along the conditional distribution looks like should be clarified in an empirical exercise.

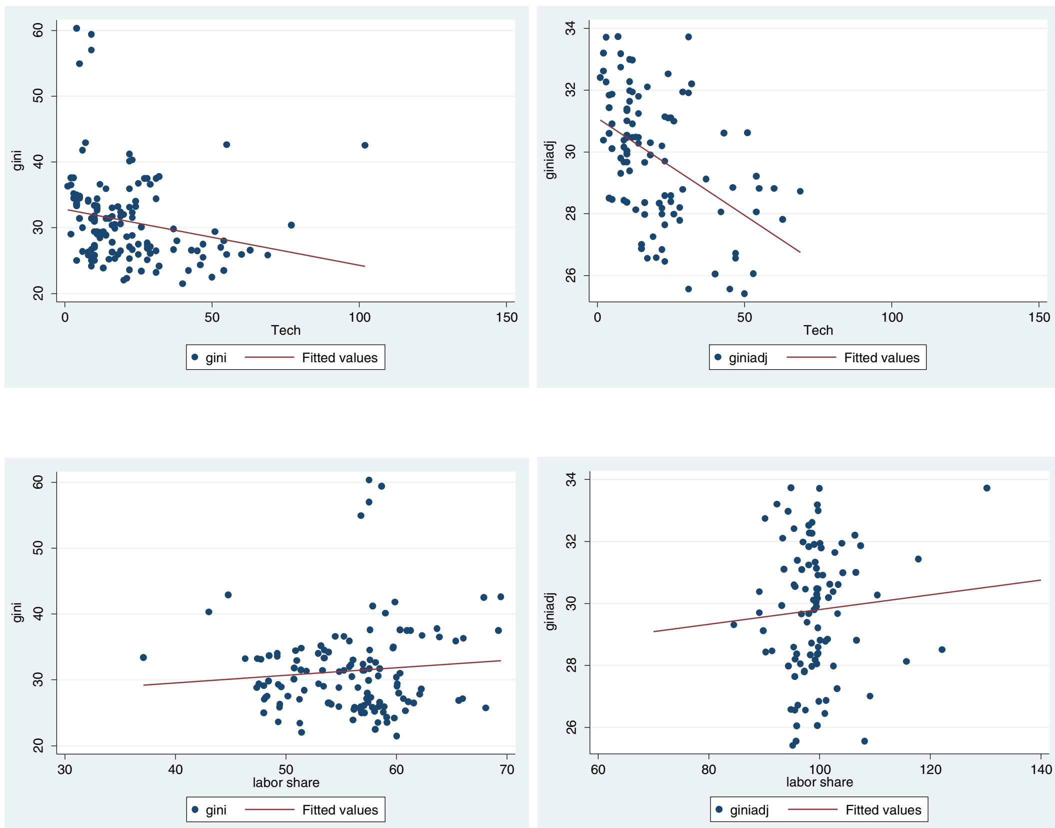

Fig. B1. Unconditional relationship between the rate of technological change (x-axis, upper plots), the labour share over income (x-axis, lower plots) and income inequality (y-axes).

Table B1
Results from quantile regressions of influence of technological change on income inequality based on baseline specification, but excluding other control variables.

	Dependent variable: Gini coefficient								
	Q10	Q20	Q30	Q40	Q50	Q60	Q70	Q80	Q90
Tech	−0.057*	−0.074*	−0.094**	−0.078**	−0.130***	−0.120**	−0.129***	−0.061***	−0.038**
	(0.030)	(0.041)	(0.031)	(0.022)	(0.030)	(0.037)	(0.051)	(0.085)	(0.113)
N. obs.	139	139	139	139	139	139	139	139	139
Pseudo R-sq.	0.046	0.020	0.039	0.067	0.075	0.072	0.053	0.016	0.011

Note: Dependent variable is the Gini index. The variables are 4-year averaged over the time span 1996–2011. ***, ** and * indicate significance level at 1%, 5% and 10%, respectively. Bootstrapped standard errors are in parenthesis.

Appendix C

Table C1
Descriptive statistics.

Variable		Mean	Std. Dev.	Min	Max			Obs.
Gini	Overall	31.0	6.7	21.5	60.3	N	=	139.0
	Between		6.5	23.2	57.9	n	=	38.0
	Within		1.5	27.4	36.5	T-bar	=	3.7
Tech	Overall	24.8	24.9	1.0	148.0	N	=	155.0
	Between		23.0	2.8	107.5	n	=	39.0
	Within		9.9	−31.2	89.8	T-bar	=	4.0
open	Overall	88.1	49.7	20.8	314.7	N	=	156.0

Table C1 (*continued*)

Variable		Mean	Std. Dev.	Min	Max			Obs.
	Between		48.4	25.1	278.3	n	=	39.0
	Within		13.1	40.4	136.3	T	=	4.0
GDPcap	Overall	23.5	13.2	1.3	79.7	N	=	155.0
	Between		12.4	2.1	64.3	n	=	39.0
	Within		4.8	4.9	38.8	T-bar	=	4.0
gov	Overall	42.2	7.8	14.3	57.5	N	=	149.0
	Between		7.3	18.3	55.0	n	=	39.0
	Within		2.5	36.4	54.6	T-bar	=	3.8
labshare	Overall	55.6	6.1	32.9	69.5	N	=	140.0
	Between		5.8	40.1	68.5	n	=	35.0
	Within		2.0	48.5	63.4	T	=	4.0
human	Overall	13.2	5.7	1.6	30.7	N	=	126.0
	Between		5.2	3.1	23.4	n	=	33.0
	Within		2.6	5.2	21.2	T-bar	=	3.8
FI	Overall	1.5	1.4	−1.5	2.5	N	=	152.0
	Between		1.2	−1.1	2.5	n	=	38.0
	Within		0.7	−0.3	3.6	T	=	4.0

Note: For a definition of the explanatory variables, see note to Table 2.

References

Acemoglu, D., 2002. Directed technological change. Rev. Econ. Stud. 69 (4), 781–809.
Acemoglu, D., 2003. Patterns of skill premia. Rev. Econ. Stud. 70 (2), 199–230.
Acs, Z.J., Audretsch, D.B., Lehmann, E.E., 2013. The knowledge spillover theory of entrepreneurship. Small Bus. Econ. 41 (4), 757–774.
Adams, R.H., 2002. Nonfarm income, inequality, and land in rural Egypt. Econ. Dev. Cult. Chang. 50 (2), 339–363.
Adams, R.H., 2004. Economic growth, inequality and poverty: estimating the growth elasticity of poverty. World Dev. 32 (12), 1986–2014.
Adams, R.H., Page, J., 2003. Poverty, inequality and growth in selected Middle East and North Africa countries, 1980–2000. World Dev. 31 (12), 2027–2048.
Adelman, I., Robinson, S., 1989. Income distribution and development. In: Chenery, H., Srinivasan, T.N. (Eds.), Handbook of Development Economics. North Holland, Amsterdam, pp. 949–1003.
Aghion, P., Bolton, P., 1992. Distribution and growth in models of imperfect capital markets. Eur. Econ. Rev. 36, 603–611.
Aghion, P., Bolton, P., 1997. A theory of trickle-down growth and development. Rev. Econ. Stud. 64, 151–172.
Aghion, P., Howitt, P., 1997. Endogenous Growth Theory. MIT Press, Cambridge, MA.
Aghion, P., Caroli, E., García-Peñalosa, C., 1999. Inequality and economic growth: the perspective of the new growth theories. J. Econ. Lit. 37 (4), 1615–1660.
Aghion, P., Bloom, N., Blundell, R., Griffith, R., Howitt, P., 2005. Competition and innovation: an inverted-U relationship. Q. J. Econ. 120 (2), 701–728.
Aghion, P., Akcigit, U., Howitt, P., 2014. What do we learn from Schumpeterian growth theory? In: Aghion, P., Durlauf, S. (Eds.), Handbook of Economic Growth. Elsevier, Amsterdam, pp. 515–563
Aghion, P., Akcigit, U., Howitt, P., 2015a. Lessons from Schumpeterian growth theory. Am. Ec. Rev. 105, 94–99.
Aghion, P., Ufuk, A., Bergeaud, A., Blundell, R., Hémous, D., 2015b. Innovation and Top Income Inequality, NBER Working Paper No. 21247.
Alcacer, J., Gittelman, M., 2006. Patent citations as a measure of knowledge flows: the influence of examiner citations. Rev. Econ. Stat. 88, 774–779.
Almeida, P., Kogut, B., 1999. Localization of knowledge and the mobility of engineers in regional networks. Manag. Sci. 45, 905–917.
Ang, J., 2010. Finance and inequality: the case of India. South. Econ. J. 76 (3), 738–761 -.
Antonelli, C., Gehringer, A., 2016. The cost of knowledge and productivity dynamics. An empirical investigation on a panel of OECD countries. In: Link, A., Antonelli, C. (Eds.), Strategic Alliances. Leveraging Economic Growth and Development. Routledge, London, pp. 155–174 ….
Antonelli, C., Quatraro, F., 2014. The effects of biased technological changes on total factor productivity: a rejoinder and new empirical evidence. J. Technol. Transf. 39, 281–299.
Aparicio, S., Urbano, D., Audretsch, D., 2016a. Institutional factors, opportunity entrepreneurship and economic growth: panel data evidence. Technol. Forecast. Soc. Chang. 102, 45–61.
Aparicio, S., Urbano, D., Gómez, D., 2016b. The role of innovative entrepreneurship within Colombian business cycle scenarios: a system dynamics approach. Futures http://dx.doi.org/10.1016/j.futures.2016.02.004 (In press).
Archibugi, D., Pietrobelli, C., 2003. The globalization of technology and its implications for developing countries. Window of opportunity or further burden. Technol. Forecast. Soc. Chang. 70, 861–883.
Atkinson, A.B., 2015. Inequality What Can Be Done? Harvard University Press, Cambridge
Atkinson, A.B., Piketty, T. (Eds.), 2007. Top Incomes Over the Twentieth Century: A Contrast Between Continental European and English Speaking Countries. Oxford University Press, Oxford.
Atkinson, A.B., Piketty, T. (Eds.), 2009. Top Incomes Over the Twentieth Century: A Global Perspective. Oxford University Press, Oxford.
Autor, D.H., Katz, L.F., Kearney, M.S., 2008. Trends in U.S. wage inequality: revising the revisionists. Rev. Econ. Stat. 90 (2), 300–323.
Barro, R.J., 2000. Inequality and growth in a panel of countries. J. Econ. Growth 5, 5–32.
Beck, T., Demirgüç-Kunt, A., Levine, R., 2007. Finance, inequality and the poor. J. Econ. Growth 12, 27–49.
Bruton, G.D., Ketchen, D.J., Ireland, R.D., 2013. Entrepreneurship as a solution to poverty. J. Bus. Ventur. 28, 683–689.
Burstein, A., Vogel, J., 2010. Globalization, technology, and the skill premium. NBER Working Papers No. 16459.
Calderón, C., Chong, A., 2001. External sector and income inequality in interdependent economies using a dynamic panel data approach. Econ. Lett. 71, 225–231.
Ceriani, L., Verme, P., 2012. The origins of the Gini index: extracts from Variabilitàe Mutabilità (1912) by Corrado Gini. J. Econ. Inequal. 10, 421–443.
Chen, S., Ravallion, M., 2001. How did the world's poorest fare in the 1990s? Rev. Income Wealth 47, 283–300.
Chen, N., Imbs, J., Scott, A., 2009. The dynamics of trade and competition. J. Int. Econ. 77, 50–62.
Chinn, M., Ito, H., 2008. A new measure of financial openness. J. Comp. Policy Anal. 10, 309–322.
Costinot, A., Vogel, J., 2010. Matching and inequality in the world economy. J. Polit. Econ. 118 (4), 747–786.
Deardoff, A.V., 2000. Factor prices and the factor content of trade revisited: what's the use? J. Int. Econ. 50 (1), 73–90.
Dollar, D., Kraay, A., 2002. Growth in good for the poor. J. Econ. Growth 7, 195–225.
Edwards, S., 1997. Trade policy, growth, and income distribution. Am. Econ. Rev. 87 (2), 205–210.
Epifani, P., Gancia, G., 2008. The skill bias of world trade. Econ. J. 118, 927–960.
Feenstra, R.C., Hanson, G.H., 1997. Foreign direct investment and the relative wages: evidence from Mexico's maquiladoras. J. Int. Econ. 42 (3–4), 371–393.
Feenstra, R.C., Hanson, G.H., 1999. The impact of outsourcing and high-technology capital on wages. Estimates for the U.S., 1979–1990. Q. J. Econ. 114 (3), 907–940.
Ferrer-i-Carbonell, A., Ramos, X., 2014. Inequality and happiness. J. Econ. Surv. 28, 1016–1027.
Fournier, J.-M., Koske, I., 2012. The determinants of earnings inequality – evidence from quantile regressions. OECD J. Econ. Stud. 1, 7–36.
Franzini, M., Pianta, M., 2016. Explaining Inequality. Routledge, London.
Galor, O., Moav, O., 2000. Ability-biased technological transition, wage inequality, and economic growth. Q. J. Econ. 115 (2), 469–497.
Gandolfo, G., 2014. International Trade Theory and Policy. Second edition. Springer, Heidelberg.
Gehringer, A., 2013. Growth, productivity and capital accumulation: the effects of financial liberalization in the case of European integration. Int. Rev. Econ. Financ. 25, 291–309.
Gordon, R.J., 2000. Does the 'New Economy' measure up to the great inventions of the past? J. Econ. Perspect. 14 (4), 49–74.
Gordon, R.J., 2012. Is U.S. economic growth over: faltering innovation and the six headwinds. NBER Working Paper No. 18315.
Griliches, Z., 1990. Patent statistics as economic indicators: a survey. J. Econ. Lit. 28, 1661–1707.
Grossman, V., 2001. Inequality, Economic Growth, and Technological Change: New Aspects in an Old Debate. Springer-Verlag, Berlin.
Guillaud, E., 2013. Preferences for redistribution: an empirical analysis over 33 countries. J. Econ. Inequal. 11, 57–78.
Helpman, E., 1997. General Purpose Technologies and Economic Growth. The MIT Press, Cambridge (MA).
Hertel, T., Zhai, F., 2006. Labor market distortions, rural-urban inequality and the opening of China's economy. Ecol. Model. 23, 76–109.
Higgins, M., Williamson, J.G., 1999. Explaining inequality the world round: cohort size, Kuznets curves, and openness. NBER Working Paper No. 7224.
Jaffe, A.B., Henderson, R., Trajtenberg, M., 1993. Geographic localization of knowledge spillovers as evidenced by patent citations. Q. J. Econ. 108, 577–598.
Jaffe, A.B., Fogarty, M.S., Banks, B.A., 1998. Evidence from patents and patent citations on the impact of NASA and other federal labs on commercial innovation. J. Ind. Econ. 46, 183–205.

Jenkins, S.P., Van Kerm, P., 2006. Trends in income inequality, pro-poor income growth, and income mobility. Oxf. Econ. Pap. 58, 531–548.
Jha, S.K., 1996. The Kuznets curve: a reassessment. World Dev. 24, 773–780.
Kaplan, S.N., Rauh, J., 2010. Wall Street and Main Street: what contributes to the rise in the highest incomes. Rev. Financ. Stud. 23, 1004–1050.
Karabarbounis, L., Neiman, B., 2014. The global decline of the labor share. Q. J. Econ. 129, 61–103.
Koenker, R., Bassett, G., 1978. Regression quantiles. Economic 461, 33–50.
Kose, A., Prasad, E., Rogoff, K., Wei, S.-J., 2009. Financial globalization: a reappraisal. IMF Staff. Pap. 56 (1), 8–62.
Kuznets, S., 1955. Economic growth and income inequality. Am. Econ. Rev. 45, 1–28.
Kuznets, S., 1963. Quantitative aspects of the economic growth of nations. Econ. Dev. Cult. Chang. 11 (2), 1–80.
Lane, P.R., Milesi-Ferretti, G.M., 2007. The external wealth of nations mark II: revised and extended estimates of foreign assets and liabilities, 1970–2004. J. Int. Econ. 73, 223–250.
Link, A.N., Siegel, D.N., 2007. Innovation Entrepreneurship and Technological Change. Oxford University Press, Oxford.
Lundberg, M., Squire, L., 2003. The simultaneous evolution of growth and inequality. Econ. J. 113, 326–344.
MacDonald, J.M., 1996. Does import competition force efficient production? Rev. Econ. Stat. 76 (4), 721–727.
Manasse, P., Turrini, A., 2001. Trade, wages, and 'superstars'. J. Int. Econ. 54, 97–117.
Martins, P.S., Pereira, P.T., 2004. Does education reduce wage inequality? Quantile regression evidence from 16 countries. Labour Econ. 11, 355–371.
Mushinsky, D.W., 2001. Using non-parametrics to inform parametric tests of Kuznets' hypothesis. Appl. Econ. Lett. 8, 77–79.
Napolitano, G., Sirilli, G., 1990. The patent system and the exploitation of inventions: results of a statistical survey conducted in Italy. Technovation 10 (1), 5–16.
Nelson, R.R., Winter, S.G., 1982. An Evolutionary Theory of Economic Change. Harvard University Press, Cambridge.
Ohinata, A., van Ours, J.C. (2012), Spillover Effects of Studying With Immigrant Students in the Same Classroom: Evidence From Quantile Regression Analysis. Tilburg University, mimeo.
Okazawa, R., 2013. Skill-biased technical change, educational choice, and labor market polarization: the U.S. versus Europe. J. Econ. Inequal. 11, 321–342.
Panagariya, A., 2000. Evaluating the factor-content approach to measuring the effect of trade on wage inequality. J. Int. Econ. 50 (1), 91–116.
Panizza, U., 2002. Income inequality and economic growth: evidence from American data. J. Econ. Growth 7, 25–41.
Piketty, T., 2014. Capital in the 21st Century. Harvard University Press, Cambridge.
Piketty, T., Saez, E., 2003. Income inequality in the United States 1913–1998. Q. J. Econ. 118, 1–41.
Popp, D., 2003. Pollution control innovations and the Clean Air Act of 1990. J. Policy Anal. Manage. 22, 641–660 (2003).
Popp, D., 2005. Lessons from patents: using patents to measure technological change in environmental models. Ecol. Econ. 54, 209–226.
Rajan, R.G., Zingales, L., 2003. The great reversals: the politics of financial development in the twentieth century. J. Financ. Econ. 69, 5–50.
Ramos, X., Van de Gaer, D., 2015. Empirical approaches to inequality of opportunity: principles, measures and evidence. J. Econ. Surv. http://dx.doi.org/10.1111/joes.12121 (In press).
Ravallion, M., 1995. Growth and poverty: evidence for developing countries in the 1980s. Ecol. Lett. 48, 411–417.
Roine, J., Vlachos, J., Waldenstrom, D., 2009. The long-run determinants of inequality: what can we learn from income data? J. Public Econ. 93, 974–988.
SanchisLlopis, J.A., et al., 2015. Good times bad times: entrepreneurship and the business cycle. Int. Entrep. Manag. J. 11, 243–251.
Schumpeter, J.A., 1934. The Theory of Economic Development: An Inquiry into Profits, Capital, Credit, Interest, and the Business Cycle. Harvard College, Cambridge MA.
Schumpeter, J.A., 1942. Capitalism Socialism and Democracy. Harper and Brothers, New York.
Solow, R.M., 1957. Technical change and the aggregate production function. Rev. Econ. Stat. 39, 312–320.
Van Zeebroeck, N., 2011. The puzzle of patent value indicators. Econ. Innov. New Technol. 20, 33–62.
Van Zeebroeck, N., van Pottelsberghe, B., 2011. The vulnerability of patent value determinants. Econ. Innov. New Technol. 20, 283–308.
Vanhoudt, P., 2000. An assessment of the macroeconomic determinants of inequality. Appl. Econ. 32, 877–883.
White, H., Anderson, E., 2001. Growth versus distribution: does the pattern of growth matter? Dev. Policy Rev. 16, 267–289.
Xu, L.C., Zou, H., 2000. Explaining the changes of income distribution in China. China Econ. Rev. 11, 149–170.

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