Innovation and Income Inequality: World Evidence

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7 February 2019

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Abstract

In this paper we explore the effect of innovation on income inequality using annual country panel data for 29 countries. We demonstrate that innovation activities reduce personal income inequality by matching patents from the European Patent Office with their inventors. Our findings are supported by instrumental variable estimations to tackle endogeneity. The results are also robust with respect to various inequality measures, alternative quality indexes of innovation, truncation bias, the use of patent applications together with granted patents and different ways to split or allocate patents.

JEL classification: D63, O30, O31, O33, O34, O40, O47

Keywords: top income inequality, overall inequality, innovation, citations, knowledge spillovers

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Acknowledgements: We would like to thank Ernest Miguelez and Rosina Moreno Serrano for their suggestions. Also we would like to thank Anastasia Litina for very helpful comments and discussions. In addition we would like to thank Evangelos Dioikitopoulos, Dimitrios Dadakas and Nikos Tsakiris as well as the participants of the 4th International Conference on Applied Theory, Macro and Empirical Finance (University of Macedonia, 2018) for their comments and suggestions. We would also like to show our gratitude to the Science, Technology and Innovation Microdatalab of OECD for providing us the data to carry out this research. Any remaining errors are ours.

1 Introduction

Since the famous work of Solow (1956) economists have been studying the issues of growth and convergence. Many years later, Mankiw et al. (1992) use cross country data to test the Solow model. Their empirical analysis confirms the implications of Solow and claims that human capital is one of the most important growth determinants. Currently, country and regional income disparities are still high on the research agenda. It has been shown that economies at similar income levels often share many common elements like: education levels, science and technology endowments, infrastructure and institutional quality (Iammarino et al., 2018). Martin (2002) finds that even though within-country inequality has increased, there is a decline in across country-income inequality. He concludes that “the best strategy to reduce world income inequalities is to induce aggregate economic growth in poor countries”. There is also a rich literature which argues that innovation is a major determinant of economic growth (Aghion and Howitt, 1992 and Aghion and Jaravel, 2015). In this paper, we conclude that innovation activities reduce personal income inequality in a world panel of countries (see also Antonelli and Gehringer, 2017).

Figure 1 illustrates the trends of our measures of innovation and inequality. We see that innovation activity has increased since 1980. At the same time, the top 1% income share rose, while Gini index has remained almost the same. The measure of innovation which increased the most was citations. Although recent studies criticize the role of citations as quality measure of innovation (Kelly et al., 2018) it still remains one of the most popular measures of quality patents.

[Insert Figure 1 here]

In Figure 2 we present a scatter plot of the log differences of citation years and top 1% income share. The countries[1] with the red label have experienced an increase in citations per capita and at the same time a drop in their top 1% income share. Five of these eight countries, belong to the top fifteen most innovative countries based on Table 2. This evidence and the work of Aghion et al. (2018) about top income inequality in USA have inspired us to test the effect of innovation on top income inequality at the country level using a world sample.

[Insert Figure 2 here]

In this paper, we conclude that innovation is negatively associated with personal income inequality. We apply the same methodology with Aghion et al. (2018) with two differences: i) our sample contains countries instead of US states ii) we use patents from EPO, while they use patents from USPTO. Initially, we use OLS regressions with country and year fixed effects to explore this relationship across different countries over time. We also apply instrumental variable estimations to check the robustness of our basic results and confirm that causality runs from innovation to income inequality. Our main contributions in the literature are three. First, we contribute to the literature on inequality and growth by studying innovation as a channel linking the two (Aghion and Howitt, 1992 and Benos and Karagiannis, 2018). Second, we enrich the research on innovation and income inequality by including many different measures of both innovation and income inequality (Aghion

[1] These countries are: USA, Japan, Australia, France, United Kingdom, Denmark, Russian Federation and Malaysia.

at el., 2018). Third, we identify an innovation network through citations based on the location of the inventors for the period 1978-1985. This knowledge based instrument helps us to tackle the endogeneity problem. Four papers are close to our work: the paper of Antonelli C. and Gehringer A. (2017), Risso and Carrera (2018), Wlodarczyk (2017) and Permana et al., (2018). Only Antonelli C. and Gehringer A. (2017) state that innovation may reduce income inequality[2]. We distinguish our paper from them by using quality measures of innovation[3] and in addition two different instruments to deal with endogeneity. To the best of our knowledge, we are the first to present robust evidence according to which there is a causal effect of innovation on income inequality at the country level.

The rest of the paper is organized as follows. Section 2 explores the relations between innovation and income distribution. Section 3 presents the data. Section 4 shows the empirical strategy. Section 5 discusses the results and Section 6 concludes.

2 Theoretical framework

2.1 Innovation and Regional Inequality

According to many studies innovation has a positive effect on income inequality using regional data. First, there is the productivity effect which boosts wages of employees who work in innovative firms (Lee, 2011). These firms are able to develop new products and as a result new jobs are created (Breau et al., 2014). The

[2] As we explain in the section 2, the other studies find positive results (Permana et al., 2018) or contradictory results for different measures of innovation (Wlodarczyk, 2017) or contradictory results for different amounts of the same measure of innovation (Risso and Carrera, 2018).
[3] Quality measures of innovations as citations capture the true impact of patents (Aghion at el., 2018).

new jobs require advanced technologies suitable only for high skilled employees and this impact shows up in their salaries (Lee, 2011 and Breau et al., 2014). Also, innovative regions lure highly skilled and highly paid workers (Lee, 2011). Paas (2012) use GDP per capita in 2007 at the NUTS 2 level as explanatory variable and human capital indicators[4], patent applications and R&D expenditures as independent variables. The cross region analysis shows that innovation has significant role in explaining regional income disparities between the EU NUTS2 regions.

The effect of innovation is stronger on top income shares than the rest of the income distribution (Aghion et al., 2018). According to them, innovation from both incumbents and entrants increases top income inequality. The difference between incumbents and entrants is that incumbents erect barriers. The barriers discourage new entrants and boost top income inequality. Pollak (2014) shows that incumbent firms defend their leading position by innovating at a high rate. His endogenous growth model justifies a persistent high growth rate by raising R&D intensity. This procedure stops only when the profits of the incumbent company fall.

Aghion et al. (2018) propose an additional channel through which innovation affects top income inequality. This channel is capital gains. The source of capital gains is the award for the innovative companies (mark-up). They indicate that through mark-up the companies have managed to increase their profits during the past forty years. Entrepreneurs and CEOs earn the bigger share of profits.

[4] The human capital indicators are: Human resources in science and technology, population with tertiary education, participation in life-long learning and employment in knowledge-intensive services.

There are empirical findings, which confirm all above arguments. Lee (2011) uses data from the European Community Household Panel for the period 1995-2001 and finds that innovation has a positive effect on income inequality. Aghion et al. (2018) conclude that innovation drives top income inequality and not the opposite in US states by applying IV regressions. The results are similar for Canadian cities (Breau et al., 2014). In addition, innovation increases the inter-city inequality. Berkes and Gaetani (2018) explore the effect of innovation on income segregation within commuting zones[5]. Their main hypothesis is whether CZs that experience an expansion in innovation and knowledge activities also experience an increase in income segregation, defined as variation of income across neighborhoods within the city. Their results suggest that more innovative cities are also cities with higher levels of earnings inequality.

Liu and Lawell (2015) support that there is a U-shaped relationship between innovation and income inequality in Chinese provinces. They state that small amounts of innovation can reduce income inequality but big amounts actually increase it following the same methodology with Lee and Pose (2013). Another paper on the effect of innovation on income inequality in China is by Fan et al. (2012) who find that innovation and inequality increased at both regional and provincial levels. In a recent study, De Paolo et al., (2018) show that innovation increases top income shares but reduces overall income inequality.

The above studies provide theoretical channels through which innovation may reduce income inequality. Innovation creates knowledge spillovers (Aghion et al.,

[5] Commuting zones are cities and Census Tracts are neighborhoods for the USA.

2018), which can benefit individuals with fewer skills (Lee and Pose, 2013). These individuals can learn from their high skilled partners and augment their productivity (Lee, 2011). They then manage to increase their salaries and income inequality falls. However the empirical studies conducted at the regional level do not confirm the above arguments. One possible explanation is that geographical proximity may not be so important factor as other forms of proximity are (Boschma, 2005). Based on this framework we construct our spillover instrument in a next section.

2.2 Innovation and Cross-Country Inequality

Antonelli C. and Gehringer A. (2017) argue that technological change can reduce income inequality. First, the creative destruction effect ruins the existing capital and wealth. Second, fast rates of technological change are associated with the creation of new firms by new entrepreneurs that are able to challenge the incumbents by the introduction of radical innovations. According to them, technological change helps increase total factor productivity and labor productivity. As a result, the wages of all individuals in the economy increase. They state that the strong price competition among companies could decrease the accumulation of rents. Economic growth reduces interest rates and this in turn causes a fall in capital gains. They conclude that in a Schumpeterian framework with fast rate of technological change the reduction of income inequality is possible. In line with this argument, Iacopetta (2005) states that fast technological change may reduce wage inequality by reducing the price of equipment. Then less skilled workers are more likely to use sophisticated technologies.

Risso and Carrera (2018) find that the level of R&D should be high enough to reduce income inequality using the Gini index from the Standardized World Income Inequality Database and R&D as a percentage of GDP from the World Development Indicators as their measure of innovation. In any other case R&D will increase income inequality. Wlodarczyk (2017) employs also R&D expenditures and finds that R&D increases income inequalities, while EPO patent applications reduce income inequalities. Permana et al., (2018) adopt also EPO patent applications as a measure of innovation and find that innovation increases income inequality. The last two papers use European country samples with similar time periods[6] and produce very different results.

Innovation may have different results in countries with dissimilar institutions. For example, Scandinavian countries prefer egalitarian societies (Acemoglu et al., 2012). Also, in contrast with many European countries, the flexible US markets allow high skilled individuals to enter innovative sectors (Lee and Pose, 2013).

Chu A. and Cozzi G. (2017) create a theoretical model about patent policy and R&D subsidies. They examine the effects of these policies on income inequality in a Schumpeterian growth framework and find that these two policies produce very contradictory results. They conclude that strengthening patent protection causes a moderate increase in income inequality whereas raising R&D subsidies causes a large decrease in income inequality. In addition Jones and Kim (2018) develop a different Schumpeterian model. They claim that there are forces which boost top income shares by increasing the productivity of entrepreneurs but other forces enhance the creative

[6] The time period for Wlodarczyk (2017) is 2005-2014 and for Permana et al., (2018) is 2003-2014.

destruction effect. They argue that globalization may increase entrepreneurs' profits but at the same time it increases competition.

2.3 Inequality and Innovation

Also inequality can affect innovation. A decrease in inequality may trigger an increase in the number of customers who can buy new products (Hatipoglu, 2012). The change in inequality can affect the inventors' expected profits and their decisions about R&D investments.

On the contrary, Tselios (2011) finds that income inequality affects positively innovation at the NUTS 1 level. He states that there two opposite effects: i) the market size effect, i.e. an unequal distribution of income is responsible for small regional markets for new products and those markets grow slowly, as only a small number of consumers can afford to buy them; ii) the price effect, which implies that inequality can boost innovation because the richest consumers are willing to buy new products (Pose and Tselios, 2010).

These papers underlie the potential endogeneity problem between innovation and income inequality, which we try to solve in a next section. In general innovation has an ambiguous effect on income inequality, which depends on the level of aggregation of the analysis. It seems that innovation increases inequality using regional data, but reduces it when employing country-level data.

3 Data

The data on pre-tax income shares of the top 10%, 1% and 0.5% income earners in our country panel analysis are drawn from the World Wealth and Income Database (Alvaredo et al., 2017). These data are available for some countries from 1870 to 2016 but we focus on the period after 1978. We have chosen the Standardized World Income Inequality Database (Frederick Solt, 2016) for the Gini index like Risso and Carrera (2018). The Standardized World Income Inequality Database provides us with 100 equivalent Gini indexes for the pre-tax income and every of these has a different standard deviation. We include in our analysis the Gini index with the smallest standard deviation.

Quantity and quality measures of innovation come from The Science, Technology and Innovation Microdatalab of OECD. It has provided us with the databases containing quality and quantity measures of innovation on EPO[7] patents. We use the OECD Patent Quality Indicators database, which includes the following quality measures of innovation: citations, claims, generality index and the family size of each patent and the OECD REGPAT database, which provides the location of inventors and applicants. Our quantity measures of innovation are the number of patents in the OECD Patent Quality Indicators database. When a patent has more than one inventor we split the patent equally among inventors (Aghion et al. 2018). We also use the applicants[8] instead of inventors as a robustness check in the Appendix. We match the quality measures of innovation with the inventors without splitting them.

[7] We use EPO databases because out of 29 countries in our sample 12 are European countries. Still, as we can see in Table 2, US have the biggest share of patents in the database and Japan is third.
[8] The name of the database is applicants but usually by applicants OECD means the firms.

We consider patents granted for our benchmark analysis. This is our first check for the quality of patents because good applications are more likely to be approved than bad ones (Régibeau and Rockett, 2010). In the Appendix we show that our results are robust even if we use the full sample (grants plus applications). In any case the number of patents is a crude measure of innovation because a patent with a great contribution to the literature and a patent with small contribution receive the same weight (Aghion et al., 2018).

For this reason, we apply quality measures of innovation, except the number of patents. The measures for our benchmark analysis are:

- Patents per capita weighted by the number of citations within i[9] years: this variable measures the number of citations received within years i after the application date (Aghion et al., 2018).
- Patents per capita weighted by the number of claims: the number of claims captures the breadth of a patent (Lerner, 1994 and Akcigit et al., 2016).
- Patents per capita weighted by their generality index. The generality index is based on a modification of the Hirschman-Herfindahl Index and uses information about the number and distribution of citations received and the Technology classes (IPC)[10] of the patents these citations come from (Squicciarini et al., 2013).

[9] The i can be 5 or 7 years. We use 5 years window in our main analysis but we apply also the 7 years window in the Appendix.
[10] They consider all IPC classes contained in the citing patent documents and account for the number and distribution of both 4-digit and n-digit IPC technology classes contained in citing patents, where n refers to the highest level of disaggregation possible (Squicciarini et al., 2013).

- Patents per capita weighted by family size. The family size is represented by the number of patent offices at which a given invention has been protected. The most valuable patents are being protected by many different patent offices (Squicciarini et al., 2013).

The time span for all our innovation measures is 1978-2015. We use the filing date of the application. We use the patents which have been granted and different quality measures of innovation. We aggregate them at the country level and then divide them by the population of each country.

Many studies focus on citation indexes. The work of Hall et al. (2001) with citation data provided economists with the necessary tools to study the technological knowledge flows between inventors, companies and regions by using the citing and the cited patent. However there are some major problems in the citation data. First, there is truncation bias due to the time lag between application and grant (Aghion et al. 2018). Even though our measures of citations do not suffer much from truncation bias[11] we provide Table A10 in the Appendix where we restrict our sample until 2007 and our results are robust. Recent studies point a second problem in citation data, which is due to the similarity between patents. For instance Kelly et al., (2018) use the example of the famous patent of Nikola Tesla in 1888 with number 381,968 about AC motor. Despite the novelty of the patent it has received only two citations. The authors develop an alternative measure of innovation which captures the novel words in the description of the patents. In our paper we use alternative measures of innovation which are not based on citation data as claims and family size for our benchmark

[11] More details about the construction of the indexes in the Appendix.

analysis and include four additional measures in the Appendix. Still citation measures are the most famous and through them we track down the spillovers for subsequent innovations (Abrams et al., 2013).

We extract the rest of the control variables from the World Bank database. We have used the domestic credit (provided by financial sector as a percentage of GDP) to control for the financial sector influence on inequality. The financial sector usually helps the inventors to innovate and increase their salaries (Aghion et al., 2018). For instance, a big share of the employees (almost 27%) who belong in the top 0.1% income share in the United States work in the financial sector or use financial services (Szymborska, 2016). The second variable is general government final consumption expenditure (% of GDP) in order to control for the effect of government size in each country. Empirical studies find that government size has a negative effect on capital income inequality and specifically on the top 1% income share (Luo et al., 2017). Next we include in our analysis GDP per capita (constant 2010 US$), because it has been found that GDP per capita has a positive effect on Gini index and the highest quintile income shares (Barro, 2008). We also control for the business cycle by using the unemployment rate (Aghion et al., 2018) and include population growth. We end up with an unbalanced panel of 29 countries over the time period 1978-2015.

4 Empirical Strategy

4.1 Estimation Methodology

Our estimation method is similar with that of Aghion et al., (2018). We take the log of our innovation measures, inequality and GDP per capita and estimate the following equation:

$$\log(y_{it}) = A + B_i + B_t + b_1 \log\left(innov_{i(t-1)}\right) + b_2 X_{it} + \varepsilon_{it}$$

where i stands for country i, t stands for time period t, y_{it} is the measure of inequality (in log), A is the constant, B_i, B_t correspond to country and year fixed effects, $innov_{i(t-1)}$ is innovation in year $t-1$ (also in log) and, X are the control variables. We use country and year fixed effects to account for permanent cross-country differences in inequality and overall changes in inequality respectively. The advantage by taking both measures of inequality and innovation in logs is that b_1 can be interpreted as the elasticity of inequality with respect to innovation. We estimate autocorrelation and heteroskedasticity robust standard errors in all regressions.

We have decided to take the one year lag of innovation as the main independent variable. Our database, Patent Quality Indicators, provides us with the application dates of the patents. We include in our analysis patents from the European Patent Office. Depalo and Addario (2014) use the EPO patents Database and find that inventors' earnings peak at $t-1$ instead of t. They assume that bureaucracy is responsible for this delay. A second empirical study of Bell (2016), who uses patents from USPTO, confirms the conclusion that inventors' income increases before the application date. In the recent study of De Palo et al., (2018), the authors apply one year lag in their innovation measure and their sample is for European regions. So, we choose the one year lag for our measures of innovation.

4.2 Endogeneity and Spillover Instrument

As it has been pointed in subsection 2.3 inequality can also boost innovation. Here, we argue that there is a casual effect from innovation on income inequality. Our first instrument accounts for the spillover effects of innovation. We claim that past innovation predicts and facilitates recent innovation. Knowledge creation boosts inequality, while knowledge diffusion through linkages and networks creates new opportunities (Iammarino et al., 2018). We build our citation network based on the location of the inventors. We want to capture the existence of spillovers among inventors (Aghion and Jaravel, 2015).

We follow the methodology of Aghion et al., (2018) to construct our spillover instrument. We use the OECD Citations database. The intuition is to instrument innovation in a country by its predicted value, based on past innovation intensities in other countries and the propensity to cite patents from these other countries (Aghion et al., 2018), (Technical details on the construction of the instrument are provided in the Appendix). A second study of Berkes and Gaetani (2018) use a similar approach with the paper of Aghion et al., (2018). They split their sample of patents in 1994 and they use the old sample (from 1985-1994) to predict innovation activity in more recent years (2005-2014).

The first point, which both studies focus on, is the geographical externalities of the instrument and the potential instrument's impact on local outcomes. Both studies are conducted at the regional level while our study is conducted at the country level. There are much longer distances among countries than in regions within countries, so we do not worry much about this problem. However someone may claim the exactly opposite that long distances among countries makes difficult the diffusion of knowledge. According to many studies geographical proximity is not the reason for knowledge spillovers or innovation diffusion. The necessary conditions for knowledge to travel are the existence of strong organizational channels (such as firms) and, dense knowledge community networks and skills and this is exactly what we aim to capture by our spillover instrument (Breschi and Lissoni, 2001; Boschma, 2005; D'Este et al., 2013).

The second point is the predicting power of the instrument for recent innovation activity. Cohen and Levinthal (1989) introduce the notion of absorptive capacity and claim that knowledge spillovers can induce complementarities in R&D efforts (Aghion and Jaravel, 2015). According to Aghion and Jaravel (2015) innovation in one country is often built on knowledge created by innovations in another country. Malerba et al., (2013) use patent data from EPO and find that international R&D spillovers are effective in fostering patenting. Citations reveal past knowledge spillovers and provide channels for future innovation (Caballero and Jaffe, 1993). Also, spillovers reduce the cost of innovation (Aghion et al., 2018). Our first stage results from Table A5 in the Appendix confirm the strength of our instrument. The coefficient of our spillover instrument is positive and significant when we use either quantity or quality measures of innovation.

A final point is the similarity between citation measures and our spillover instrument. The spillover network can be very different at different lags between citing and cited patent (Acemoglu et al., 2016). Also we apply additional robustness checks in Table A7 of the Appendix. Our instrument is based on the links between citing and cited patents until 1985. We exclude from the sample first all years before 1985 and then all years before 1987 to eliminate any doubts. Our measures of innovation remain significant. We take the one year lag of our instrument like (Aghion et al., 2018) to avoid any concerns about demand shocks.

4.3 Robustness Checks

In this section, we apply a second instrument as a robustness check. Our second instrument is the log of "charges for the use of intellectual property, receipts (BoP, current US$)" from International Monetary Fund. Our argument is that countries which possess patents of high quality are going to receive bigger amounts of money for the authorized use of proprietary rights such as patents, trademarks, copyrights, industrial processes and designs including trade secrets and franchises. This is the first reason why we are interested on the receipts and not payments. Intellectual property rights have a positive effect on measures of innovation. Strong protection stimulates innovative activity and increases innovation incentives (Kanwar and Evenson, 2003 and Beladi et al., 2016). Kanwar and Evenson (2003) find that intellectual property protection has a positive effect on R&D expenditures, while Beladi et al., (2016) claim that strategic IPRs enforcement can be used as an effective instrument to subsidize contractual R&D. Dutta and Sharma (2008) test the effect of intellectual property rights on Indian firms and find that not only IPR increases R&D expenditures but also facilitates patenting by India in the U.S. Chu et al., (2017) explores the effect of IPR on China and conclude that IPR has a positive effect on innovation. Branstetter et al. (2005) use U.S. multinational firms' data and find limited evidence that IPR boosts domestic innovation. Also Chu and Cozzi (2017) state that patent protection and R&D subsidies are two important policy instruments that determine technological progress and economic growth. Aghion et al., (2015) find that the product market reform, which took place in EU in 1992, facilitated innovative investments in manufacturing industries of countries with strong patent rights. They found a complementarity between competition and patent protection by using a theoretical and an empirical model. This policy helped the industries with strong patent rights to increase their R&D investments. The literature confirms the positive relationship between IPR and innovation.

Next we examine if this instrument is exogenous to income inequality. Here is the second reason why we use receipts. The "charges for the use of intellectual property, receipts" come from non-residents. At the country level this means that this amount of money enters the domestic market from a foreign country. So, we believe that this instrument correlates directly only with our measures of innovation and it is unlikely to affect other domestic variables. To avoid any suspicions that our variable could potential affect indirectly our measures of inequality we use the lead of the variable as instrument. By using the $\boldsymbol{t+3}$ periods for our instrument we believe that the case for it being exogenous with regard to income inequality in period $\boldsymbol{t}$ is even stronger. There is a second reason for using the $\boldsymbol{t+3}$ value of our instrument. The average time for a patent to be granted in the EPO was almost 4 years in the 2005 (45.3 months, source: EPO official website). So, we apply the $\boldsymbol{t-1}$ year to the application date in our model and use $\boldsymbol{t+3}$ years of our instrument.

5 Results

5.1 Summary Statistics and OLS Results

In this section we present the results from both OLS and IV regressions. All variables are defined in Table 1. We provide the sample of countries in Table 2 sorted both by the number of patents and top income share. Then, we present summary statistics in Table 3. In Table 4 we provide descriptive statistics for the measures of innovation and inequality for two distinctive years. It is clear that there is a significant increase in the means of our measures of inequality from 1985 to 2005. Also the minimum and maximum values have increased over these years. We reach the same conclusion also from the table with the innovation measures.

[Insert Table 1 here]

[Insert Table 2 here]

[Insert Table 3 here]

[Insert Table 4 here]

Next, we provide the results from OLS regressions. Table 5 regresses the top 1% income share on our measures of innovation with a 1-year lag. We see that all our measures of innovation have a significant and negative effect on top 1% income share as we expect from theory. We have taken the logs for both measures of innovation and top 1% income share so that we can interpret the coefficient of innovation as elasticity. A 1% increase in the number of citations is associated with a 0.0225% decrease of the top 1% income share. The rest of the variables in column 2 have the expected signs. In Table A2 of the Appendix we use clustered standard errors at the country level to allow for correlation within countries. The citations within a 5-year window keep the negative effect but at the 5% level of significance. We also provide in Tables A3-A4 of the Appendix alternative measures of innovation as robustness checks with robust and clustered standard errors respectively.

[Insert Table 5 here]

In Table 6, we test the effect of innovation on different measures of inequality. It is clear from this Table that innovation influences top income shares. We provide the most widely used measures of overall inequality and Gini index. Innovation has a negative coefficient, so innovation reduces not only top income but also overall income inequality.

[Insert Table 6 here]

5.2 IV Results

In Table 7 we present evidence after we use the spillover instrument. We see that now all measures of innovation are significant and have a negative effect on the top 1% income share. For instance a 1% increase in the citations within a 5 year window is associated with a 0.0402% fall of the top income share. In Table A8 of the Appendix we apply alternative measures of innovation with the spillover instrument and the effect is again negative and significant.

[Insert Table 7 here]

Next, in Table 8 we present our results when we use as instrument the charges of intellectual property rights. A 1% increase in the citations within a 5 year window reduces the top 1% income share by 0.0813%. Again in Table A9 we provide different measures of innovation with our second instrument and the results confirm the negative and significant effect of innovation.

[Insert Table 8 here]

In Table 9 we use both our instruments. Again we show that innovation measures have a negative impact on top income inequality. Our test statistics confirm that our instruments are appropriate.

Table 10 regresses the various measures of inequality on our measure of innovation (citation on a 5-year window). Innovation influences negatively the top 10% and top 0.5% income shares. Also, we see in column 5 that citations have a negative and significant effect on the Gini index. In Table A11 of the Appendix we use claims as measures of innovation and the spillover instrument. We get similar results as in Table 10.

[Insert Table 10 here]

5.3 Additional Findings and Discussion

Like Aghion et al. (2018) the magnitude of the coefficient of citations (column 2) in Table 7 is much bigger than the corresponding coefficient in column 2 in Table

5. Aghion et al. (2018) state that a good reason could be the interaction between innovation and competition. This explanation is based on the inverted-U relationship between these two variables (Aghion et al., 2005).

The government size and unemployment rate are also significant and with the expected signs. Both variables are in percentages (between 0-1) and indicate that a 1% increase in the government size, decreases the top 1% income share by 2.383% (Table 7), while the same increase in unemployment rate increases the top 1% income share by 0.959% (column 2). In contrast with Aghion et al. (2018) we find strong evidence that government size and unemployment rate have the strongest effects, while the financial sector has a weaker effect. This is not surprising if we consider that in our sample 12 out of 29 countries are European. Even though Nickell (1997) states that there are big differences among European countries, we cannot ignore the fact that unemployment rate is very high in Europe (Fanti and Gori, 2011) and many European countries (high GDP countries) have higher than the optimal level of government size compatible with GDP growth rate maximization (Forte and Magazzino, 2011).

In the Second Appendix we present additional IV results when we use the full sample of patents[12] and also when we match patents with applicants. More details about the construction of these databases can be found in the Appendix. We apply both our instruments in these regressions. We use the full sample in Table S2 and the applicants in Table S4 of the Second Appendix. Again the effect of innovation on income inequality is negative and significant.

[12] When we say full sample we mean also applications that have been not granted.

6 Conclusions

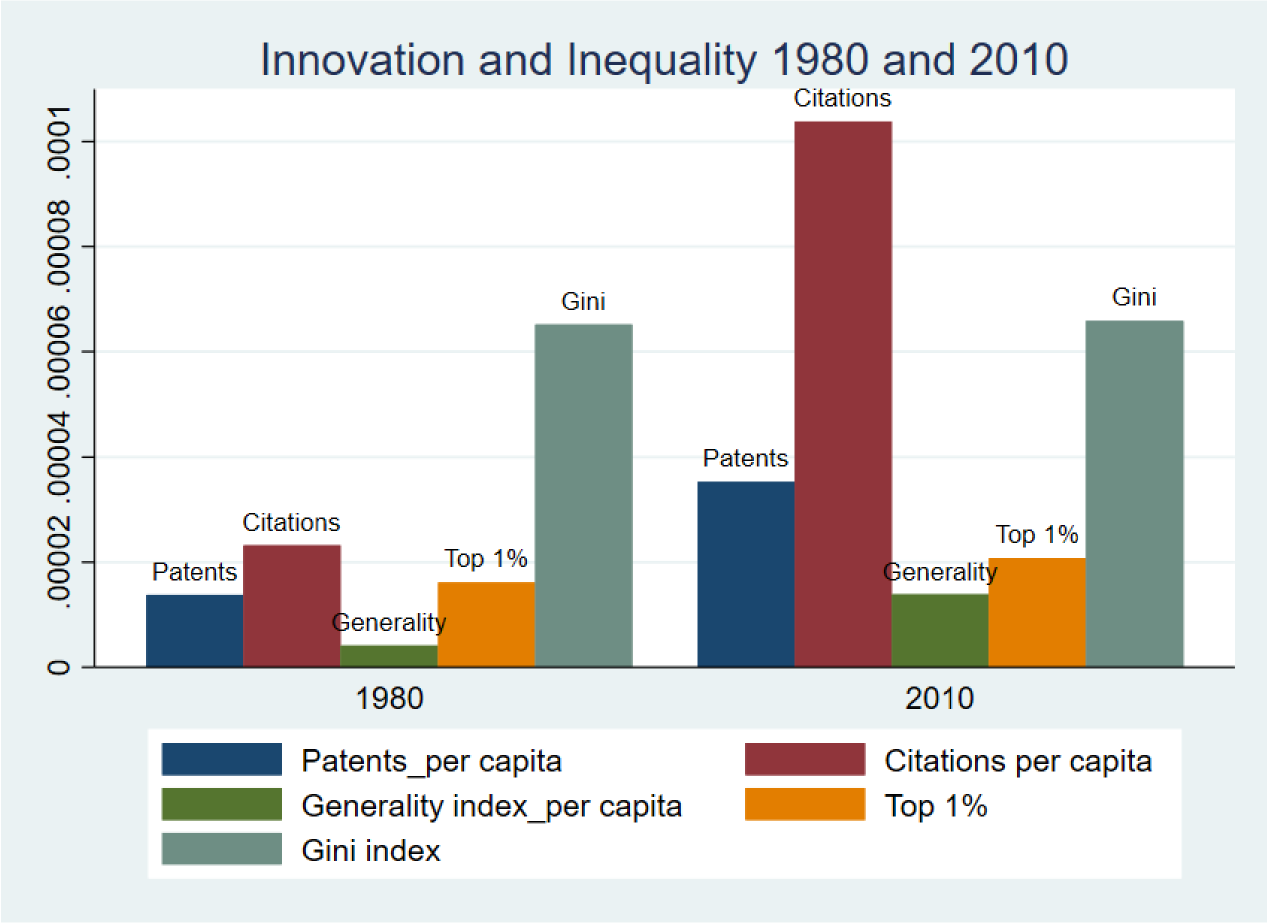
To the best of our knowledge, we make the first attempt to explore the effect of innovation on top income shares at the country level and provide robust evidence accounting for endogeneity. In addition, our results are robust with respect to alternative inequality measures, quality indexes of innovation, truncation bias, the use of patent applications together with the granted patents and different ways to split or allocate the patents.

We identify a network of inventors through citations and our spillover instrument predicts recent innovation activity. We show that knowledge can be transferred between countries. The mobility of the inventors is a very crucial topic because they contribute to the diffusion of knowledge between different places (Miguelez., 2013 and Miguelez., 2018) .

Our analysis concludes that innovation reduces personal income disparities within countries. We find strong evidence that innovation reduces top income inequality using various top income shares. When we test the effect of innovation on overall inequality, we also find strong evidence that innovation reduces it. Our analysis is also based on various quantity and quality measures of innovation. Quality measures of innovation take into consideration the magnitude of the novel inventions in contrast with the quantity measures. We have showed also that innovation affects inequality and not the opposite by applying IV analysis. We could not explore the relationship between innovation and top income shares for a longer time period due to the limited data on income shares[13] at the country level. Finally, an extension of the analysis could include property rights Tebaldi and Elmslie (2013) or taxation Akcigit et al. (2016) as additional control variables.

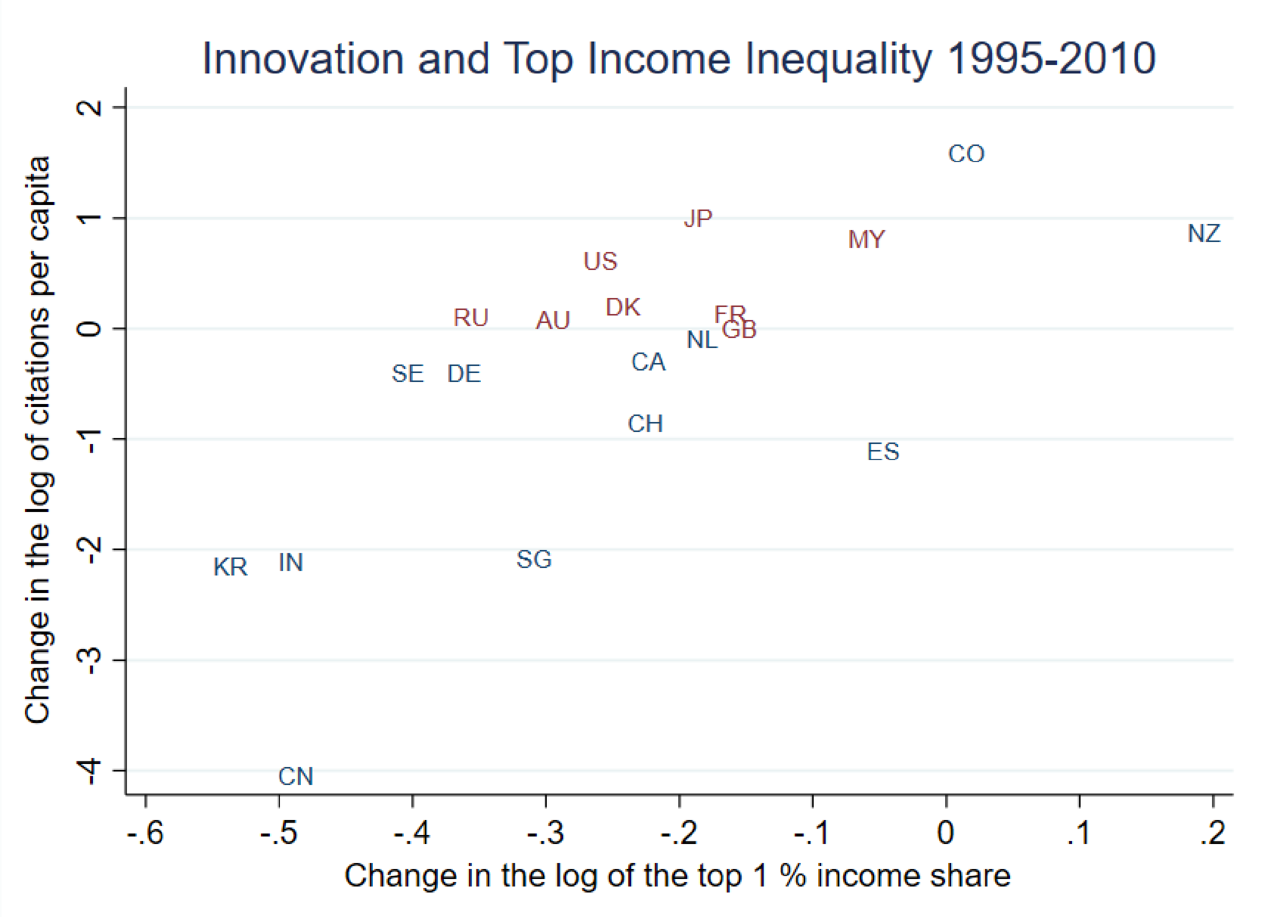
[13] Higher top income shares than 1% like 0.5% or 0.01%.

FIGURE 1



Notes: Measures of Innovation per capita and Inequality in two distinctive years. We divided the measures of inequality by 10000. Number of citations received within 5 years of the application date. Source: OECD Patent Quality Database and WID.

FIGURE 2



Notes: This figure illustrates the difference of the log of the number of citations per capita against the difference of the log of the top 1% income share in 1995 and 2010. The countries with the red labels exhibit an increase in the number of citations and a decrease in the top 1% income share. Number of citations received within 5 years of the application date. Source: OECD Patent Quality Database and WID.

TABLE 1
Variable description and notation

Variable names	Description
	Measures of Inequality
Top i%	Share of income own by the top i% (i being equal to 10, 1 and 0.5) of the income distribution. Time: 1960-2016. Source: WID.
Gini	Gini index of inequality with the smallest standard deviation. Time: 1960-2016. Source: SWIID.
	Measures of innovation
Patent	Total number of patent granted by the EPO per capita. Time: 1978-2015. Source: OECD.
Cit(i)	Total number of citations received no longer than i=5 or i=7 years after applications per capita. Time: 1978-2015. Source: OECD.
Claims	Total number of claims per capita. Time: 1978-2015. Source: OECD.
Generality Index	Total number of patents weighted by the Generality index per capita. Time 1978-2015. Source: OECD.
Family	The number of patent offices at which a given invention has been protected per capita. Time: 1978-2015. Source: OECD.
Grant lag	The time elapsed between the filing date of the application and the date of the grant per capita. Time: 1978-2015. Source: OECD.
Renewal	The count of years during a patent has been renewed per capita. Time: 1978-2015. Source: OECD.
Patent Scope	The scope of a patent in terms of the number of distinct 4-digit subclasses of the International Patent Classification per capita. Time: 1978-2015. Source: OECD.
Many fields	Dummy variable that takes the value 1 if the patent is allocated to other fields per capita. Time: 1978-2015. Source: OECD.
	Control Variables
Popgr	Growth of total population. Time: 1960-2015. Source: World Bank.
Gvtsize	General government final consumption expenditure (% of GDP). Time: 1960-2015. Source: World Bank.
Unemployment	Unemployment, total (% of total labor force) (national estimate). Time: 1960-2015. Source: World Bank.
Gdppc	Real GDP per capita in US $ (in log). Time: 1960-2015. Source: World Bank.
Finance	Domestic credit provided by financial sector (% of GDP). Time: 1960-2015. Source: World Bank.
	Instruments
Charges	Charges for the use of intellectual property, receipts (BoP, current US$). Time: 1960-2015. Source: International Monetary Fund.
Spillover	Links between citing and cited patent. Time: 1978-1985. Source: OECD Citations database, March 2018.

TABLE 2

Countries sorted by top income share and number of patents granted

Country Code	Top 1% Income Share	Country Code	Patents
BR	0.2769	**US**	9131.182
LB	0.2303	**DE**	8997.221
TR	0.2043	**JP**	7318.001
CO	0.1957	**FR**	3330.792
RU	0.1695	**GB**	1984.298
US	0.1586	**IT**	1528.121
AR	0.1436	**CH**	1179.77
IN	0.1401	**NL**	1053.845
ZA	0.1383	**SE**	866.688
SG	0.1208	**KR**	612.8299
DE	0.1180	**CA**	479.5446
CA	0.1157	**DK**	323.7587
GB	0.1096	**CN**	311.5027
CN	0.1052	**ES**	261.8465
FR	0.0979	**AU**	213.376
JP	0.0955	**IN**	88.22777
CH	0.0946	**RU**	74.56846
ES	0.0907	**IE**	61.33867
KR	0.0890	**TR**	47.05082
MY	0.0887	**ZA**	44.95966
IE	0.0839	**BR**	40.76601
IT	0.0808	**SG**	38.51117
NZ	0.0769	**NZ**	32.57962
PT	0.0766	**PT**	16.06893
SE	0.0688	**AR**	10.3987
AU	0.0684	**MY**	9.806165
NL	0.0603	**CO**	2.062382
DK	0.0543	**LB**	1.516281
MU	0.0540	**MU**	0.78125

Notes: The left column illustrates the countries sorted by the mean of top 1 percent income share over the period 1978-2015 while the right column represents the countries sorted by the mean number of patents granted over the period 1978-2015. Codes and Names: AR (Argentina), AU (Australia), BR (Brazil), CA (Canada), CH (Switzerland), CN (China), CO (Colombia), DE (Germany), DK (Denmark), ES (Spain), FR (France), GB (United Kingdom), IE (Ireland), IN (India), IT (Italy), JP (Japan), KR (South Korea), LB (Lebanon), MU (Mauritius), MY (Malaysia), NL (Netherlands), NZ (New Zealand), PT (Portugal), RU (Russian Federation), SE (Sweden), SG (Singapore), TR (Turkey), US (United States), ZA (South Africa).

TABLE 3
Summary statistics of the main variables

Basic Variables	**Observations**	**Mean**	**Standard Deviation**
Innovation			
Patents	1,020	1414.559	2957.226
Cits5	1,020	4610.21	11841.81
Claims	1,020	43768.22	103913.3
Generality Index	1,020	637.4894	1553.293
Family_size	1,020	24936.44	57135.35
Inequality			
Top 10%	736	0.3431062	0.0810591
Top 1%	806	0.1082087	0.0517032
Top 0.5%	797	0.078386	0.0431325
Gini index	1040	0.4668933	0.0627005
Control Variables			
Gdppc	1079	24664.8	18003.09
Government	1071	16.75752	4.588026
Finance	1042	106.3674	62.0598
Unemployment	958	7.40703	4.537359
Popgrowth	1101	1.004564	0.8874716
Instruments			
Spillover per capita	982	2.55E-06	5.38E-06
Charges (in log,3 years lead)	773	19.67748	0.8874716
Additional Innovation Variables			
Cits7	1,020	5974.502	15417.47
Grant_lag	1,020	6894717	1.69E+07
Rrenewal	1,020	39311.05	94200.98
Patent_scope	1,020	7440.13	17219.43
Many_field	1,020	1658.817	3885.518

Notes: Summary statistics for the main variables calculated over the period 1978-2015. GDP per capita is calculated in $ per capita. The additional innovation variables appear only in the Appendix.

TABLE 4
Descriptive statistics of measures of Innovation and Inequality

	Mean	**P25**	**P50**	**P75**	**Min**	**Max**
1985						
Patents	1024.213	4.9999	47.1671	818.4558	2.25	6474.606
Citations	3148.68	10	65	1796	2	23886
Claims	21908.16	87	717	11689	30	153255
Generality Index	477.6779	2.635417	13.7908	272.5453	1.48	3542.336
Family_size	14736.48	133	715	9840	36	99721
Top 10%	0.299593	0.2719911	0.2990886	0.3362401	0.2237018	0.36657
Top 1%	0.0757316	0.0550965	0.075687	0.09051	0.0438392	0.12553
Top 0.5%	0.0511046	0.0347679	0.0528679	0.0618155	0.0269458	0.09316
Gini Index	0.4533452	0.4135882	0.4355646	0.4796089	0.3504605	0.6278827
2005						
Patents	2175.706	75.2403	471.2052	1915.728	4.5667	13827.53
Citations	8087.41	145	1115	7820	15	76995
Claims	82155.78	3092	16792	80443	47	691068
Generality Index	965.4901	11.05057	177.5321	778.7822	3.363457	7880.999
Family_size	41917.85	1648	8052	39926	42	352949
Top 10%	0.3683359	0.3165537	0.3777983	0.4185774	0.1396149	0.550825
Top 1%	0.1341594	0.0940248	0.1153626	0.1838664	0.049756	0.2780328
Top 0.5%	0.0983904	0.0642	0.0848751	0.1247931	0.0359116	0.2242774
Gini Index	0.4722523	0.4442616	0.4761565	0.4951895	0.3352951	0.6380104

Notes: Summary statistics includes mean, percentile thresholds, minimum and maximum for our measures in two distinctive years.

TABLE 5
Innovation and Top 1% Income Share-OLS Results

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Dependent Variable	Top1%	Top1%	Top1%	Top1%	Top1%
Measures of Innovation	Patents	Cit5	Claims	Generality	Family
Innovation	-0.0503***	-0.0225***	-0.0248***	-0.0229***	-0.0227***
	(-3.45)	(-3.43)	(-3.75)	(-3.19)	(-3.10)
Popgr	0.0166	0.0167	0.0171	0.0161	0.0163
	(1.44)	(1.46)	(1.47)	(1.38)	(1.40)
Gvtsize	-2.520***	-2.567***	-2.524***	-2.581***	-2.558***
	(-5.66)	(-5.87)	(-5.76)	(-5.88)	(-5.80)
Unemployment	0.826***	0.809***	0.822***	0.794***	0.795***
	(3.18)	(3.11)	(3.15)	(3.06)	(3.02)
Gdppc	0.265***	0.255***	0.269***	0.243***	0.252***
	(5.66)	(5.81)	(6.08)	(5.59)	(5.31)
Finance	0.0473**	0.0505**	0.0487**	0.0533**	0.0480**
	(2.05)	(2.21)	(2.13)	(2.30)	(2.07)
Observations	665	665	665	665	665
R^2	0.940	0.940	0.941	0.940	0.940

Notes: Innovation is taken in logs and lagged by one year. The dependent variable is the log of the top 1% income share. Panel data OLS regressions with country and year fixed effects. Time span: 1979-2015. Autocorrelation and heteroskedasticity robust standard errors are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

TABLE 6
Citation and Different Measures of Inequality-OLS results

	(1)	**(2)**	**(3)**	**(4)**
Dependent Variables	Top10%	Top1%	Top0.5%	Gini
Cit5	-0.0109***	-0.0225***	-0.0257***	-0.00937***
	(-2.95)	(-3.43)	(-2.92)	(-6.55)
Popgr	-0.00500	0.0167	0.000370	0.00782**
	(-0.74)	(1.46)	(0.03)	(2.18)
Gvtsize	-0.184	-2.567***	-2.515***	-0.591***
	(-0.74)	(-5.87)	(-4.70)	(-5.78)
Unemployment	0.917***	0.809***	0.667**	0.674***
	(6.32)	(3.11)	(2.03)	(8.32)
Gdppc	0.183***	0.255***	0.266***	0.0686***
	(7.46)	(5.81)	(4.48)	(4.75)
Finance	0.0184	0.0505**	-0.0242	0.0548***
	(1.26)	(2.21)	(-0.86)	(9.39)
Observations	633	665	564	856
R^2	0.933	0.940	0.946	0.897

Notes: Innovation is taken in logs and lagged by one year. The dependent variables are the log of different measures of inequality. Panel data OLS regressions with country and year fixed effects. Time span: 1979-2015. Autocorrelation and heteroskedasticity robust standard errors are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

TABLE 7
Innovation and Top 1% Income Share using Spillover Instrument-IV results

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Top1%	Top1%	Top1%	Top1%	Top1%
Measures of Innovation	Patents	Cit5	Claims	Generality	Family
Innovation	-0.0923***	-0.0402***	-0.0403***	-0.0432***	-0.0440***
	(-3.32)	(-3.30)	(-3.36)	(-3.30)	(-3.33)
Popgr	0.0105	0.0103	0.0110	0.00940	0.00977
	(0.93)	(0.95)	(0.96)	(0.84)	(0.86)
Gvtsize	-2.251***	-2.383***	-2.379***	-2.354***	-2.314***
	(-4.73)	(-5.21)	(-5.23)	(-5.11)	(-4.94)
Unemployment	1.008***	0.959***	0.949***	0.954***	0.963***
	(3.60)	(3.49)	(3.45)	(3.46)	(3.42)
Gdppc	0.399***	0.372***	0.370***	0.366***	0.388***
	(4.55)	(4.62)	(4.71)	(4.67)	(4.59)
Finance	0.0280	0.0345*	0.0319	0.0386*	0.0287
	(1.35)	(1.70)	(1.56)	(1.85)	(1.39)
Observations	641	641	641	641	641
R^2	0.698	0.698	0.700	0.696	0.695
F-first stage	45.79	49.66	51.53	56.74	48.63
Groups	27	27	27	27	27

Notes: Innovation is taken in logs and lagged by one year. The dependent variable is the log of the top 1% income share. Panel data 2SLS regressions with country and year fixed effects. Time span: 1979-2014. The lag between the spillover instrument and the endogenous variables is set to 1 year. Autocorrelation and heteroskedasticity robust standard errors are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

TABLE 8
Innovation and Top 1% Income Share using Charges as an Instrument-IV results

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Top1%	Top1%	Top1%	Top1%	Top1%
Measures of Innovation	Patents	Cit5	Claims	Generality	Family
Innovation	-0.247**	-0.0813***	-0.0723***	-0.0951***	-0.0825***
	(-2.28)	(-2.80)	(-2.82)	(-2.63)	(-2.67)
Popgr	-0.0198	-0.0144	-0.0166	-0.0186	-0.0198
	(-1.60)	(-1.29)	(-1.46)	(-1.50)	(-1.64)
Gvtsize	-1.712**	-2.108***	-2.192***	-2.121***	-2.117***
	(-2.22)	(-3.61)	(-4.19)	(-3.66)	(-3.66)
Unemployment	2.207**	1.635***	1.537***	1.825***	1.543***
	(2.49)	(2.87)	(2.92)	(2.84)	(2.71)
Gdppc	1.056**	0.764***	0.680***	0.799***	0.735***
	(2.53)	(3.22)	(3.29)	(3.02)	(3.10)
Finance	0.0248	0.0487*	0.0279	0.0461	0.0261
	(0.79)	(1.65)	(1.04)	(1.50)	(0.94)
Observations	512	512	512	512	512
R^2	0.569	0.666	0.700	0.655	0.663
F-first stage	8.90	18.21	24.07	17.66	17.41
Groups	28	28	28	28	28

Notes: Innovation is taken in logs and lagged by one year. The dependent variable is the log of the top 1% income share. Panel data 2SLS regressions with country and year fixed effects. Time span: 1979-2014. The lead between the instrument based on charges and the endogenous variables is set to 3 years. Autocorrelation and heteroskedasticity robust standard errors are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

TABLE 9

Innovation and Top 1% Income Share using two instruments-IV results

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Dependent Variable	Top1%	Top1%	Top1%	Top1%	Top1%
Measures of Innovation	Patents	Cit5	Claims	Generality	Family
Innovation	-0.106***	-0.0433***	-0.0409***	-0.0445***	-0.0440***
	(-2.81)	(-2.85)	(-2.93)	(-2.81)	(-2.88)
Popgr	-0.0142	-0.0124	-0.0138	-0.0135	-0.0155
	(-1.38)	(-1.20)	(-1.32)	(-1.26)	(-1.47)
Gvtsize	-2.122***	-2.227***	-2.263***	-2.256***	-2.194***
	(-4.26)	(-4.61)	(-4.89)	(-4.79)	(-4.53)
Unemployment	1.434***	1.276***	1.272***	1.317***	1.253***
	(3.31)	(3.24)	(3.25)	(3.33)	(3.15)
Gdppc	0.533***	0.477***	0.446***	0.453***	0.464***
	(3.53)	(3.67)	(3.85)	(3.75)	(3.71)
Finance	-0.00113	0.0142	0.00359	0.00899	0.00174
	(-0.04)	(0.52)	(0.14)	(0.33)	(0.07)
Observations	495	495	495	495	495
R^2	0.734	0.741	0.747	0.744	0.739
F-first stage	24.89	27.99	35.32	38.66	28.73
Sargan-Hansen (p-value)	0.4807	0.5393	0.6261	0.4263	0.6215
Groups	26	26	26	26	26

Notes: Innovation is taken in logs and lagged by one year. The dependent variable is the log of the top 1% income share. Panel data 2SLS regressions with country and year fixed effects. Time span: 1979-2012. The lag between the spillover instrument and the endogenous variables is set to 1 and the lead between the charges instrument and the endogenous variables is set to 3 years. Autocorrelation and heteroskedasticity robust standard errors are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

TABLE 10

Citation and Different Measures of Inequality using Spillover Instrument-IV results

	(1)	**(2)**	**(3)**	**(4)**
Dependent Variables	Top10%	Top1%	Top0.5%	Gini
Cit5	-0.0122*	-0.0402***	-0.0271*	-0.0145***
	(-1.71)	(-3.30)	(-1.70)	(-4.10)
Popgr	-0.00923	0.0103	-0.00449	0.00530
	(-1.48)	(0.95)	(-0.35)	(1.46)
Gvtsize	-0.309	-2.383***	-2.491***	-0.478***
	(-1.34)	(-5.21)	(-4.54)	(-4.38)
Unemployment	0.878***	0.959***	0.605*	0.681***
	(6.18)	(3.49)	(1.85)	(7.41)
Gdppc	0.190***	0.372***	0.287***	0.100***
	(4.07)	(4.62)	(2.63)	(4.33)
Finance	0.00916	0.0345*	-0.0283	0.0505***
	(0.74)	(1.70)	(-1.02)	(8.65)
Observations	619	641	552	825
R^2	0.643	0.698	0.702	0.450
F-first stage	46.54	49.66	39.51	91.84
Groups	25	27	25	28

Notes: Innovation is taken in logs and lagged by one year. The dependent variables are the log of different measures of inequality. Panel data 2SLS regressions with country and year fixed effects. Time span: 1979-2014 for columns 1, 2, 3 and 1979-2015 for column 4. The lag between the spillover instrument and the endogenous variables is set to 1 year. Autocorrelation and heteroskedasticity robust standard errors are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Appendix

A. Construction of the Main Database

We use patents and inventors from EPO to construct our databases. First we extract the Quality indicators from the Quality Database of OECD (Squicciarini et al., 2013). This database contains 3,190,373 patents. The 1,529,776 out of 3,190,373 were granted. For our benchmark analysis we include in the sample only the granted patents. This dataset contains quality indexes of innovation like citations within 5- and 7- year windows, claims, generality index, family size, grant lag, renewal, patent scope and many fields. In our basic analysis we apply the citations in a 5- year window, claims, generality index and family size as Aghion et al. (2018). We test the effect of 5 additional measures of innovation (citation in a 7- year window, grant lag, renewal, patent scope and many fields) on top 1% income share to robustify our results. Our quality measures of innovation do not suffer from truncation bias because they have normalized according to the maximum value received by patents in the same year-and-technology cohort (Squicciarini et al., 2013). In any case we restrict our sample of patents until 2015.

Our additional quality measures of innovation contain information about the issue speed, the value and the complexity of the patent. Specifically:

- Patents per capita weighted by the grant lag index: The logic of this index is that the most important patents are granted faster than the less important ones (Régibeau and Rockett, 2010).
- Patents per capita weighted by the renewal index: This index shows that the most valuable patents are renewed for longer periods (Pakes, 1986).

- Patents per capita weighted by the patent scope index: The scope of patents is associated with the technological breadth and economic value of patents (Lerner, 1994).
- Patents per capita weighted by the many fields index: This index shows if the patent is allocated to more than one field.

More details about the construction of the indexes can be found in "Measuring Patent Quality: Indicator of Technological and Economic Value", Squicciarini et al., 2013.

We match the patents with their inventors from the REGPAT database[14]. We manage to allocate 1,526,891 out of 1,529,776 (99% matching) to their inventors. REGPAT contains a variable, reg_share, which shows how much precise is the location of the inventor. We include only inventors with reg_share more than 70%. Our final database has 3,861,884 observations over the time period 1978-2015. After we exclude also the countries that do not have data about inequality we end up with 3,665,830 observations. We provide the share of patents for every country in the Table A1. We call this database: Database 1.

B. Construction of Additional Databases

In order to check the robustness of our results we construct two additional databases. First, we follow the same methodology as in the previous section but this time we have included all patents and not just patents granted. According to Abrams et al., (2013) many companies create patent applications (defensive patents) to erect barriers for the new entrants, especially in fields of rapid development. If our quality

[14] Every time we want to match a patent database of OECD with REGPAT we use the appln_id which is the Patent application identifier (PATSTAT, October 2012).

measures of patents are good proxies for radical innovation then they should take into consideration this fact because defensive patents should have received fewer citations.

We now use the full sample of observations from the Quality Database of OECD. Again we allocate the patents to their inventors from the REGPAT database. We manage to match 3,175,990 patents out of 3,190,373 (99% matching). Again we apply the same restrictions as in the previous section and end up with 7,686,937 observations over the time period 1978-2015. The share of applications for every country exists in Table S1. We call this database: Database 2.

In our final database we change the matching method. We keep just the patents that have been granted but instead of inventors we allocate the patents to their applicants[15]. The rest of the methodology remains the same. We match 1,529,724 patents out of 1,529,776. After we apply the same restrictions to the database we end up with 1,544,772 observations over the time period 1978-2015. The share for every country appears in Table S3. We call this database: Database 3.

C. Construction of the Spillover Instrument

We follow the same methodology with Aghion et al., (2018) to build our spillover instrument. First we construct the relative weight of country *j* in the citations with lag *k* of patents granted in country *i*, aggregated over the period 1978-1985[16].

$$w_{i,j,k} = \sum_{t=1978}^{1985} m(i,j,t,k) \Big/ \sum_{t=1978}^{1985} \sum_{l\#i} m(i,l,t,k)$$

[15] As we notice by applicants the OECD refers to companies.
[16] The OECD Citations database contains cited patents from 1836.

This is a matrix of weights, where for each pair of countries (i,j), and for each lag k between citing and cited patents (we restrict the k to be between three and ten years), wi,j,k denotes the relative weight.

Next we create our instrument as follows:

$$KS_{i,t} = {}^{1}/_{Pop_{-i,t}} \sum_{k=3}^{10} \sum_{j \neq i} w_{i,j,k} innov(j, t - k)$$

where $Pop-i,t$ is the population of countries but not the country i, $m(i,j,t,k)$ represents the number of citations from a patent in country i, with an application date t to a patent of country j filed k years before t, and $innov(j,t-k)$ is our measure of innovation in country j at time $t-k$ and the log of KS is the instrument. To reduce the risk of simultaneity, we set a one-year time lag between the endogenous variable and this instrument. We normalize by $Pop-i,t$, as otherwise our measure of spillovers would mechanically put at a relative disadvantage a country the population of which grows faster than the others.

We use the OECD Citations database for this instrument and specifically the EP_CITATIONS dataset. This dataset contains 11,795,845 links between citing and cited patents from EPO. We use the REGPAT database to match the patents with their inventors. After the merge our database has 45,692,954 observations.

TABLE A1
Share of patents for every country in Database 1

Code	Share	Code	Share
AR	0.02%	**JP**	22.43%
AU	0.49%	**KR**	1.99%
BR	0.11%	**LB**	0.00%
CA	1.28%	**MU**	0.00%
CH	2.52%	**MY**	0.03%
CN	0.9%	**NL**	2.39%
CO	0.00%	**NZ**	0.08%
DE	22.78%	**PT**	0.04%
DK	0.72%	**RU**	0.2%
ES	0.68%	**SE**	1.84%
FR	7.54%	**SG**	0.1%
GB	4.46%	**TR**	0.11%
IE	0.16%	**US**	25.5%
IN	0.34%	**ZA**	0.09%
IT	3.21%		

Notes: CO has 158 patents, LB has 58 patents and MU has 9 patents. Time Period: 1978-2015

TABLE A2
Innovation and Top 1% Income Share with clustered standard errors-OLS Results

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Dependent Variable	Top1%	Top1%	Top1%	Top1%	Top1%
Measures of Innovation	Patents	Cit5	Claims	Generality	Family
Innovation	-0.0503**	-0.0225**	-0.0248**	-0.0229*	-0.0227*
	(-2.19)	(-2.10)	(-2.39)	(-1.98)	(-1.99)
Popgr	0.0166	0.0167	0.0171	0.0161	0.0163
	(0.70)	(0.72)	(0.74)	(0.68)	(0.71)
Gvtsize	-2.520**	-2.567***	-2.524**	-2.581***	-2.558***
	(-2.75)	(-2.77)	(-2.70)	(-2.82)	(-2.82)
Unemployment	0.826	0.809	0.822	0.794	0.795
	(1.24)	(1.22)	(1.23)	(1.19)	(1.19)
Gdppc	0.265***	0.255***	0.269***	0.243***	0.252***
	(3.77)	(3.70)	(3.97)	(3.45)	(3.54)
Finance	0.0473	0.0505	0.0487	0.0533	0.0480
	(0.89)	(0.97)	(0.94)	(1.01)	(0.90)
Observations	665	665	665	665	665
R^2	0.940	0.940	0.941	0.940	0.940

Notes: Innovation is taken in logs and lagged by one year. The dependent variable is the log of the top 1% income share. Panel data OLS regressions with country and year fixed effects. Time span: 1979-2015. Autocorrelation and heteroskedasticity clustered standard errors are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

TABLE A3
Alternative measures of Innovation and Top 1% Income Share-OLS results

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Dependent Variable	Top1%	Top1%	Top1%	Top1%	Top1%
Measures of Innovation	Cit7	Grant Lag	Renewal	Patents Scope	Many Fields
Innovation	-0.0237***	-0.0256***	-0.0266***	-0.0267***	-0.0273***
	(-3.56)	(-3.64)	(-3.82)	(-3.86)	(-3.83)
Popgr	0.0168	0.0166	0.0165	0.0170	0.0164
	(1.48)	(1.44)	(1.44)	(1.48)	(1.44)
Gvtsize	-2.558***	-2.550***	-2.541***	-2.534***	-2.547***
	(-5.86)	(-5.81)	(-5.78)	(-5.78)	(-5.85)
Unemployment	0.824***	0.848***	0.855***	0.860***	0.848***
	(3.15)	(3.24)	(3.26)	(3.30)	(3.25)
Gdppc	0.263***	0.275***	0.281***	0.281***	0.278***
	(5.90)	(5.81)	(6.00)	(6.02)	(6.10)
Finance	0.0496**	0.0489**	0.0477**	0.0473**	0.0499**
	(2.18)	(2.14)	(2.09)	(2.07)	(2.20)
Observations	665	665	665	665	665
R^2	0.941	0.941	0.941	0.941	0.941

Notes: Innovation is taken in logs and lagged by one year. The dependent variable is the log of the top 1% income share. Panel data OLS regressions with country and year fixed effects. Time span: 1979-2015. Autocorrelation and heteroskedasticity robust standard errors are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

TABLE A4

Alternative measures of Innovation and Top 1% Income Share with clustered standard errors-OLS results

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Top1%	Top1%	Top1%	Top1%	Top1%
Measures of Innovation	Cit7	Grant Lag	Renewal	Patent Scope	Many Fields
Innovation	-0.0237**	-0.0256**	-0.0266**	-0.0267**	-0.0273**
	(-2.14)	(-2.28)	(-2.38)	(-2.44)	(-2.36)
Popgr	0.0168	0.0166	0.0165	0.0170	0.0164
	(0.74)	(0.73)	(0.72)	(0.74)	(0.71)
Gvtsize	-2.558**	-2.550***	-2.541**	-2.534***	-2.547***
	(-2.76)	(-2.78)	(-2.74)	(-2.78)	(-2.80)
Unemployment	0.824	0.848	0.855	0.860	0.848
	(1.24)	(1.27)	(1.28)	(1.29)	(1.27)
Gdppc	0.263***	0.275***	0.281***	0.281***	0.278***
	(3.75)	(3.85)	(3.95)	(4.05)	(3.99)
Finance	0.0496	0.0489	0.0477	0.0473	0.0499
	(0.96)	(0.94)	(0.92)	(0.91)	(0.97)
Observations	665	665	665	665	665
R^2	0.941	0.941	0.941	0.941	0.941

Notes: Innovation is taken in logs and lagged by one year. The dependent variable is the log of the top 1% income share. Panel data OLS regressions with country and year fixed effects. Time span: 1979-2015. Autocorrelation and heteroskedasticity clustered standard errors are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

TABLE A5

Innovation First Stage-IV Results

	(1)	(2)	(3)	(4)	(5)	(6)
Measures of Innovation	Patents	Cit5	Patents	Cit5	Patents	Cit5
Spillover	0.118***	0.270***			0.067***	0.159***
	(6.77)	(7.05)			(5.18)	(4.98)
Charges			0.130***	0.396***	0.174***	0.450***
			(2.98)	(4.27)	(4.30)	(5.07)
Popgr	0.0160	0.0323	-0.0487	-0.0816	-0.070*	-0.1247
	(0.34)	(0.33)	(-1.24)	(-0.88)	(-1.67)	(-1.32)
Gvtsize	5.361***	9.013**	5.359***	11.440***	5.508***	11.014***
	(2.97)	(2.28)	(2.91)	(2.88)	(3.25)	(3.00)
Unemployment	3.627***	7.098***	6.527***	12.824***	6.012***	11.104***
	(3.75)	(3.19)	(5.68)	(4.96)	(5.91)	(4.78)
Gdppc	2.602***	5.307***	3.649***	7.515***	3.349***	6.875***
	(16.00)	(14.50)	(16.47)	(15.79)	(17.72)	(16.11)
Finance	-0.0799	-.0223	0.1200	0.659***	0.162*	0.759***
	(-1.02)	(-0.12)	(1.13)	(2.72)	(1.78)	(3.65)
Observations	641	641	512	512	495	495
Groups	27	27	28	28	26	26

Notes: Innovation is taken in logs and lagged by one year. The dependent variable is the log of the top 1% income share. Panel data 2SLS regressions with country and year fixed effects. Time span: 1979-2014 for columns 1 and 2 and 1979-2012 for columns 3, 4, 5 and 6. First stage results of Spillover and Charges instrument on Innovation. The lag between our spillover instrument and our measures of innovation is set to one year and the lead between our instrument based on the charges and our measures of innovation is set to 3 years. Autocorrelation and heteroskedasticity robust standard errors are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

TABLE A6

Innovation and Top 1% Income Share by splitting equally the quality measures

	(2)	(1)	(4)	(3)	(6)	(5)
Dependent Variable	Top1%	Top1%	Top1%	Top1%	Top1%	Top1%
Measures of Innovation	Cit5	Claims	Cit5	Claims	Cit5	Claims
Innovation	-0.0446***	-0.0423***	-0.0965***	-0.0939**	-0.0495***	-0.0459***
	(-3.25)	(-3.34)	(-2.58)	(-2.54)	(-2.79)	(-2.87)
Popgr	0.00934	0.0112	-0.0182	-0.0176	-0.0142	-0.0138
	(0.84)	(0.97)	(-1.52)	(-1.51)	(-1.37)	(-1.32)
Gvtsize	-2.336***	-2.311***	-2.039***	-1.965***	-2.187***	-2.190***
	(-4.97)	(-4.96)	(-3.17)	(-3.14)	(-4.36)	(-4.58)
Unemployment	0.995***	0.993***	1.878***	1.859***	1.398***	1.363***
	(3.52)	(3.55)	(2.75)	(2.78)	(3.27)	(3.30)
Gdppc	0.390***	0.378***	0.864***	0.846***	0.519***	0.484***
	(4.50)	(4.66)	(2.93)	(2.87)	(3.54)	(3.70)
Finance	0.0341*	0.0313	0.0397	0.0267	0.00871	0.000649
	(1.66)	(1.51)	(1.30)	(0.93)	(0.32)	(0.02)
Observations	641	641	512	512	495	495
R^2	0.692	0.698	0.621	0.650	0.730	0.742
F-first stage	45.09	48.04	13.83	14.59	23.71	30.89
Hansen	-	-	-	-	0.5611	0.5489
Groups	27	27	28	28	26	26

Notes: Innovation is taken in logs and lagged by one year. The dependent variable is the log of the top 1% income share. Panel data 2SLS regressions with country and year fixed effects. Time span: 1979-2014 for columns 1 and 2 and 1979-2012 for columns 3, 4, 5 and 6. The lag between the spillover instrument and the endogenous variables is set to 1 year for columns 1 and 2 and the lead between the charges instrument and the endogenous variables is set to 3 years for columns 3 and 4. We apply both instruments in columns 5 and 6. Measures of innovation are equally split among inventors. Autocorrelation and heteroskedasticity robust standard errors are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

TABLE A7

Innovation and Top 1% Income Share Time Restrictions

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Top1%	Top1%	Top1%	Top1%	Top1%	Top1%
Measures of Innovation	Patents	Cit5	Claims	Patents	Cit5	Claims
Innovation	-0.0758**	-0.0320**	-0.0329**	-0.0693*	-0.0293*	-0.0298*
	(-2.15)	(-2.14)	(-2.17)	(-1.68)	(-1.66)	(-1.69)
Popgr	0.000898	0.00160	0.00129	0.00346	0.00362	0.00282
	(0.08)	(0.14)	(0.11)	(0.30)	(0.32)	(0.24)
Gvtsize	-2.388***	-2.444***	-2.472***	-2.137***	-2.193***	-2.186***
	(-4.89)	(-5.07)	(-5.19)	(-4.11)	(-4.24)	(-4.26)
Unemployment	0.817**	0.778**	0.762**	0.681**	0.638*	0.611*
	(2.52)	(2.44)	(2.43)	(1.99)	(1.93)	(1.90)
Gdppc	0.390***	0.364***	0.361***	0.395***	0.376***	0.370***
	(3.82)	(4.00)	(4.10)	(3.57)	(3.75)	(3.89)
Finance	0.0281	0.0332	0.0316	0.00961	0.0143	0.0128
	(1.39)	(1.64)	(1.56)	(0.50)	(0.73)	(0.66)
Observations	568	568	568	537	537	537
R^2	0.653	0.653	0.656	0.627	0.628	0.632
F-first stage	27.86	31.55	32.86	28.14	30.73	33.79
Groups	27	27	27	27	27	27

Notes: In this table we eliminate the common time periods between our instrument and our measure of innovation as a robustness check. Innovation is taken in logs and lagged by one year. The dependent variable is the log of the top 1% income share. Panel data 2SLS regressions with country and year fixed effects. Time span: 1985-2014 for columns 1, 2 and 3 and 1987-2014 for columns 4, 5 and 6. The lag between the spillover instrument and the endogenous variables is set to 1 year. Autocorrelation and heteroskedasticity robust standard errors are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

TABLE A8

Alternative measures of Innovation and Top 1% Income Share using Spillover Instrument-IV results

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Dependent Variable	Top1%	Top1%	Top1%	Top1%	Top1%
Measures of Innovation	Cit7	Grant Lag	Renewal	Patent Scope	Many Field
Innovation	-0.0402***	-0.0431***	-0.0424***	-0.0416***	-0.0423***
	(-3.31)	(-3.36)	(-3.36)	(-3.39)	(-3.40)
Popgr	0.0104	0.00973	0.00989	0.00978	0.00912
	(0.97)	(0.88)	(0.90)	(0.90)	(0.85)
Gvtsize	-2.404***	-2.388***	-2.395***	-2.387***	-2.404***
	(-5.30)	(-5.23)	(-5.26)	(-5.31)	(-5.40)
Unemployment	0.967***	1.004***	0.989***	0.981***	0.979***
	(3.51)	(3.59)	(3.55)	(3.57)	(3.58)
Gdppc	0.370***	0.390***	0.386***	0.379***	0.373***
	(4.65)	(4.63)	(4.63)	(4.70)	(4.74)
Finance	0.0335*	0.0321	0.0306	0.0293	0.0330
	(1.65)	(1.57)	(1.49)	(1.44)	(1.63)
Observations	641	641	641	641	641
R^2	0.700	0.700	0.701	0.703	0.703
F-first stage	50.02	50.53	52.13	53.73	58.33
Groups	27	27	27	27	27

Notes: Innovation is taken in logs and lagged by one year. The dependent variable is the log of the top 1% income share. Panel data 2SLS regressions with country and year fixed effects. Time span: 1979-2014. The lag between the spillover instrument and the endogenous variables is set to 1 year. Autocorrelation and heteroskedasticity robust standard errors are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

TABLE A9

Alternative measures of Innovation and Top 1% Income Share using Charges as an Instrument-IV results

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Dependent Variable	Top1%	Top1%	Top1%	Top1%	Top1%
Measures of Innovation	Cit7	Grant Lag	Renewal	Patent Scope	Many Field
Innovation	-0.0790***	-0.0795***	-0.0795***	-0.0800***	-0.0909**
	(-2.88)	(-2.79)	(-2.79)	(-2.73)	(-2.54)
Popgr	-0.0132	-0.0194	-0.0193*	-0.0176	-0.0187
	(-1.22)	(-1.63)	(-1.65)	(-1.52)	(-1.57)
Gvtsize	-2.158***	-2.225***	-2.209***	-2.224***	-2.159***
	(-3.89)	(-4.22)	(-4.13)	(-4.24)	(-3.82)
Unemployment	1.596***	1.611***	1.597***	1.635***	1.762***
	(2.89)	(2.88)	(2.86)	(2.87)	(2.79)
Gdppc	0.736***	0.721***	0.724***	0.717***	0.783***
	(3.34)	(3.25)	(3.25)	(3.18)	(2.91)
Finance	0.0449	0.0306	0.0292	0.0272	0.0386
	(1.57)	(1.12)	(1.08)	(1.01)	(1.30)
Observations	512	512	512	512	512
R^2	0.671	0.684	0.688	0.682	0.661
F-first stage	20.14	20.75	20.64	20.41	16.36
Groups	28	28	28	28	28

Notes: Innovation is taken in logs and lagged by one year. The dependent variable is the log of the top 1% income share. Panel data 2SLS regressions with country and year fixed effects. Time span: 1979-2014. The lead between the instrument based on charges and the endogenous variables is set to 3 years. Autocorrelation and heteroskedasticity robust standard errors are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

TABLE A10
Innovation and Top Income Inequality controlling for truncation bias-IV results

Dependent Measures	(1) Top1% Patents	(2) Top1% Cit5	(3) Top1% Patents	(4) Top1% Cit5	(5) Top1% Patents	(6) Top1% Cit5	(7) Top1% Patents	(8) Top1% Cit5
Innovation	-0.0931***	-0.0400***	-0.251**	-0.0841***	-0.0979***	-0.0420***	-0.218*	-0.0795**
	(-3.15)	(-3.16)	(-2.11)	(-2.58)	(-3.05)	(-3.06)	(-1.95)	(-2.24)
Popgr	0.00848	0.00849	-0.0205	-0.0163	0.0124	0.0102	-0.0228	-0.0227*
	(0.73)	(0.75)	(-1.61)	(-1.38)	(0.89)	(0.77)	(-1.55)	(-1.65)
Gvtsize	-2.311***	-2.457***	-1.870**	-2.202***	-2.175***	-2.297***	-1.952***	-2.073***
	(-4.58)	(-5.09)	(-2.42)	(-3.61)	(-3.84)	(-4.20)	(-2.59)	(-3.09)
Unemployment	1.034***	0.974***	2.195**	1.643***	1.010***	0.922***	1.920*	1.442**
	(3.46)	(3.32)	(2.29)	(2.62)	(2.99)	(2.78)	(1.88)	(1.96)
Gdppc	0.402***	0.374***	1.060**	0.781***	0.358***	0.331***	0.860*	0.669**
	(4.35)	(4.47)	(2.29)	(2.88)	(3.53)	(3.56)	(1.91)	(2.16)
Finance	0.0274	0.0342	0.0200	0.0502	0.0326	0.0375	0.0239	0.0487
	(1.28)	(1.61)	(0.60)	(1.59)	(1.16)	(1.34)	(0.62)	(1.34)
Observations	586	586	471	471	520	520	405	405
R^2	0.686	0.687	0.549	0.649	0.667	0.666	0.592	0.652
F-first stage	43.49	48.93	7.97	16.39	38.83	44.90	8.70	14.35
Groups	27	27	28	28	27	27	26	26

Notes: Innovation is taken in logs and lagged by one year. The dependent variable is the log of the top 1% income share. Panel data 2SLS regressions with country and year fixed effects. Time span: 1979-2010 for columns 1, 2, 3, 4 and 1979-2007 for columns 5, 6, 7, 8. The spillover instrument is used in columns 1, 2 and 5, 6 and the charges instrument in columns 3, 4 and 7, 8. The lag between the spillover instrument and the endogenous variables is set to 1 year and the lead between the charges instrument and endogenous variables is set to 3 years. Autocorrelation and heteroskedasticity robust standard errors are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

TABLE A11
Claims and Different Measures of Inequality using Spillover Instrument-IV results

Dependent Variables	(1) Top10%	(2) Top1%	(3) Top0.5%	(4) Gini
Claims	-0.0125*	-0.0403***	-0.0270*	-0.0149***
	(-1.70)	(-3.36)	(-1.71)	(-4.12)
Popgr	-0.00890	0.0110	-0.00318	0.00537
	(-1.40)	(0.96)	(-0.23)	(1.41)
Gvtsize	-0.290	-2.379***	-2.494***	-0.443***
	(-1.23)	(-5.23)	(-4.52)	(-4.02)
Unemployment	0.875***	0.949***	0.624*	0.691***
	(6.12)	(3.45)	(1.88)	(7.61)
Gdppc	0.191***	0.370***	0.285***	0.102***
	(4.02)	(4.71)	(2.65)	(4.33)
Finance	0.00839	0.0319	-0.0288	0.0501***
	(0.67)	(1.56)	(-1.03)	(8.55)
Observations	619	641	552	825
R^2	0.639	0.700	0.699	0.456
F-first stage	45.61	51.53	41.96	89.01
Groups	25	27	25	28

Notes: Innovation is taken in logs and lagged by one year. The dependent variables are the log of different measures of inequality. Panel data 2SLS regressions with country and year fixed effects. Time span: 1979-2014 for columns 1, 2, 3 and 1979-2015 for column 4. The lag between the spillover instrument and the endogenous variables is set to 1 year. Autocorrelation and heteroskedasticity robust standard errors are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

References

Abrams D., Akcigit U., and Popadak J., "Patent Value and Citations: Creative Destruction or Strategic Disruption?" NBER Working Paper No. 19647, 2013.

Acemoglu D., Robinson J., and Verdier T., "Can't we all be more like Scandinavians? Asymmetric growth and institutions in an interdependent world", NBER Working Paper No. 18441, 2012.

Acemoglu D., Akcigit U., and Kerr W., "Innovation Network", Proceedings of the National Academy of Sciences, 113, 2016, 11483–11488.

Aghion P., and Howitt P., "A Model of Growth Through Creative Destruction", Econometrica, Vol.60, No.2, (1992), 323-351.

Aghion P., Bloom N. A., and Blundell R., "Competition and Innovation: An Inverted-U Relationship", Quarterly Journal of Economics, 120, (2005), 701–728.

Aghion P., and Jaravel X., "Knowledge Spillovers, Innovation and Growth*", The Economic Journal, 125, (2015), 533-573.

Aghion P., Howitt P., and Prantl S., "Patent rights, product market reforms, and innovation", Journal of Economic Growth, 20, (2015), 223-262.

Aghion P., Akcigit U., Bergeaud A., Blundell R., and Hemous D., "Innovation and Top Income Inequality", Review of Economic Studies, 0, 1–45. Published by Oxford University Press on behalf of The Review of Economic Studies Limited, (2018).

Akcigit U., Baslandze S., and Stantcheva S., "Taxation and the International Mobility of Inventors", American Economic Review, 106(10), (2016), 2930-2981.

Alvaredo F., Atkinson A., Chancel L., Piketty T., Saez E., and Zucman G., "Distributional National Accounts (DINA) Guidelines: Concepts and Methods used in WID.world", WID. world working paper series No. 2016/1, (2017).

Antonelli C., and Gehringer A., "Technological change, rent and income inequalities: A Schumpeterian approach", Technological Forecasting & Social Change, 155, (2017) 85-98.

Barro R., "Inequality and Growth Revisited",Working Paper Series on Regional Economic Integration no.11, Asian Development Bank, (2008).

Beladi H., Marjit S., Xu X., and Yang L., "Strategic Enforcement, Intellectual Property Rights, and Contractual R&D", Economic Inquiry, Vol. 54, No. 4, (2016), 1904-1917.

Bell A., Chetty R., Jaravel X., Petkova N., and Reenen J., "The Lifecycle of Inventors", Working Paper, SSRN Electronic Journal, (2016).

Benos N., and Karagiannis S., "Inequality and Growth in the United States: Why Physical and Human Capital Matter", Economic Inquiry, Vol. 56, No. 1, (2018), 572-619.

Berkes E., and Gaetani R., "Income Segregation and Rise of the Knowledge Economy", Meeting Papers 213, Society for Economic Dynamics, (2018).

Boschma, R. A., "Proximity and innovation. A critical assessment", Regional Studies, 39, (2005), 61–74.

Branstetter L., Fisman R., and Foley C., "Do Stronger Intellectual Property Rights Increase International Technology Transfer? Empirical Evidence from U.S. Firm-Level Data", NBER Working Paper No. 11516, (2005).

Breau S., Kogler D., and Bolton K., "On the Relationship between Innovation and Wage Inequality: New Evidence from Canadian Cities", Economic Geography 90(4), (2014), 351–373.

Breschi, S., and Lissoni, F., "Knowledge spillovers and local innovation systems: a critical survey", Industrial and Corporate Change, 10, 975–1005, (2001).

Caballero R., and Jaffe A., “How High are the Giants' Shoulders: An Empirical Assessment of Knowledge Spillovers and Creative Destruction in a Model of Economic Growth”, NBER Macroeconomics Annual 1993, Volume 8, Chapter pages in book: (p. 15 - 86), 1993.

Chu A., Shen G., and Zhang X., “Imports and Intellectual Property Rights on Innovation in China”, Fudan University, MPRA Paper, No. 81706, 2017.

Chu A., and Cozzi G., “Effects of Patents versus R&D Subsidies on Income Inequality”, MPRA Paper, No. 83483, 2017.

Cohen W.M., and Levinthal D.A., “Innovation and learning: two faces of R&D”, Economic Journal, 99, 1989, 569-596.

De Palo C., Karagiannis S., and Raab R., “Innovation and inequality in the EU: for better or for worse?”, EUR 29303 EN, Publications Office of the European Union, Luxembourg, 2018.

Depalo D., and Addario S., “Shedding Light on Inventors' Returns to Patents” Development Working Papers 375, Centro Studi Luca d'Agliano, University of Milano, 2014.

D’Este P., Guy F., and Iammarino S., “Shaping the formation of university industry research collaborations: what type of proximity does really matter?”, Journal of Economic Geography, 13, 2013, 537–558.

Dutta A., and Sharma S., “Intellectual Property Rights and Innovation in Developing Countries: Evidence from India”, Georgetown University, International Finance Corporation (The World Bank Group), 2008.

Fan P., Wan G., and Lu M., ”China’s Regional Inequality in Innovation Capability”, China & World Economy, Vol. 20, No.3, 2012, 16-36.

Fanti L., and Gori L., “A Note on Trade Unions, Unemployment Insurance and Endogenous Growth”, Eastern Economic Journal, 37, 2011, 270-280.

Forte F., and Magazzino C., “Optimal Size Government and Economic Growth in EU Countries”, Economica Politica, a. XXVIII, n. 3, 2011.

Galbraith J., Halbach B., and Shams A., “Updated Estimates for the World Economy from the University of Texas Inequality Project”, University of Texas, UTIP-UNIDO Data Set, 2013.

Hall B. H., Jaffe A. B., and Trajtenberg M., "The NBER Patent Citation Data File: Lessons, Insights and Methodological Tools." NBER Working Paper 8498, 2001.

Hatipoglu O., “The relationship between inequality and innovative activity: a Schumpeterian theory and evidence from cross-country data”, Scottish Journal of Political Economy, Vol. 59, No. 2, 2012.

Iacopetta M., “Technological Progress and Inequality: An Ambiguous Relationship”, Available at SSRN, doi: 10.2139/ssrn. 822964, 2005.

Iammarino S., Rodríguez-Pose A., and Michael Storper, “Regional inequality in Europe: evidence, theory and policy implications”, Journal of Economic Geography, 2018, pp. 1–26.

Jones C. I., and Kim J., “A Schumpeterian Model of Top Income Inequality”, Journal of Political Economy, vol. 126, no.5, 2018.

Kanwar S., and Evenson R., “Does intellectual property protection spur technological change?”, Oxford Economic Papers 55, 2003, 235-264.

Kelly B., Papanikolaou D., Seru A., and Taddy M., “Measuring Technological Innovation over the Long Run”, NBER Working Paper, No.25266, 2018.

Lee N., “Are innovative regions more unequal? Evidence from Europe”, Environment and Planning C: Government and Policy 2011, volume 29, 2011, pages 2 – 23.

Lee N., and Pose A., “Innovation and spatial inequality in Europe and USA”, Journal of Economic Geography 13, 2013, pp. 1–22.

Lerner J., “The Importance of Patent Scope: An Empirical Analysis”, RAND Journal of Economics, 25(2), 1994, 319-333.

Liu Q., and Lawell L., “The effects of innovation on income inequality in China”, Shandong Province Educational Department, 2015.

Luo W., Pickering A., and Monteiro P., “Inequality and the Size of Government”, Discussion Papers in Economics No. 17/02, University of York, 2017.

Malerba F., Mancusi M., and Montobbio F., “Innovation, international R&D spillovers and the sectoral heterogeneity of knowledge flows”, Review of World Economics, 149, 2013, 697-722.

Mankiw G., Romer D., and Weil D., “A Contribution to the Empirics of Economic Growth”, The Quarterly Journal of Economics, Vol. 107, No. 2, 1992, pp. 407-437.

Martin S., “The Disturbing “Rise” of Global Income Inequality”, NBER Working Paper No. 8904, 2002.

Miguelez E., “How does geographical mobility of inventors influence network formation?”, WIPO Economics & Statistics Series, Working Paper No.7, 2013.

Miguelez E., “Inventor Diasporas and the Internationalization of Technology”, World Bank Group, Policy Research Working Paper, No. 7619, 2018.

Nickell S., “Unemployment and Labor Market Rigidities: Europe versus North America”, Journal of Economic Perspectives, Volume 11, Number 3, 1997, Pages 55–7.

OECD Patent Quality Indicators database, March 2018.

OECD REGPAT database, March 2018.

OECD Citations database, March 2018.

Paas T., “Regional Disparities And Innovations In Europe”, ERSA conference papers ersa12p80, European Regional Science Association, 2012.

Pakes, A., “Patents as Options: Some Estimates of the Value of Holding European Patent Stocks”, Econometrica, 54(4), 1986, 755-784.

Permana M. Y., Lantu D. C., and Suharto Y., “The effect of innovation and technological specialization on income inequality”, Problems and Perspectives in Management, 16(4), 2018, 51-63.

Pose A., and Tselios V., “Inequalities in income and education and regional economic growth in Western Europe” The Annals of Regional Science 44, 2010, 349-75.

Pollak A., “Rising R&D Intensity and Economic Growth”, Economic Inquiry, Vol.52, No.4, 2014, 1427-1445.

Régibeau P., and Rockett K., “Innovation Cycles and Learning at the Patent Office: Does the Early Patent Get the Delay?”. The Journal of Industrial Economics, volume lviii, no.2, 2010.

Risso W., and Carrera E., “On the impact of innovation and inequality in economic growth”, Economics of Innovation and New Technology, 2018.

Solow R., “A Contribution to the Theory of Economic Growth”, The Quarterly Journal of Economics, Vol. 70, No. 1, 1956, pp. 65-94.

Solt F., “The Standardized World Income Inequality Database”, Social Science Quarterly 97, 2016.

Squicciarini M., Dernis H., and Criscuolo C., “Measuring Patent Quality: Indicators of Technological and Economic Value”, OECD Science, Technology and Industry Working Papers, 2013/03, OECD Publishing, 2013.

Szymborska H., “Financial Sector Transformation and Income Inequality- An Empirical Analysis”, Financial Internet Quarterly„ e-Finanse” 2016, vol.12/ nr 2, s., 2016, 36-48.

Tebaldi E., and Elmslie B., “Does Institutional Quality Impact Innovation? Evidence from Cross-Country Patent Grant Data”, Applied Economics, vol. 45, issue 7, 2013, 887-900.

The World Bank, World Development Indicators, Data files: World Bank national accounts data, 2018.

Tselios V., “Is Inequality Good for Innovation?”, International Regional Science Review, 34(1), 2011, 75-101.

Wlodarczyk J., “Innovations and income inequalities – a comparative study”, Journal of International Studies, 10(4), 2017, 166-178.

Supplementary Appendix

TABLE S1
Share of applications for every country in Database 2

Code	Share	Code	Share
AR	0.03%	**JP**	19.80%
AU	0.67%	**KR**	3.09%
BR	0.13%	**LB**	0.00%
CA	1.55%	**MU**	0.00%
CH	2.29%	**MY**	0.03%
CN	1.66%	**NL**	2.47%
CO	0.01%	**NZ**	0.12%
DE	18.93%	**PT**	0.06%
DK	0.75%	**RU**	0.24%
ES	0.84%	**SE**	1.71%
FR	6.45%	**SG**	0.17%
GB	4.53%	**TR**	0.13%
IE	0.20%	**US**	30.68%
IN	0.55%	**ZA**	0.09%
IT	2.82%		

Notes: LB has 146 patents and MU has 24 patents. Time Period: 1978-2015

TABLE S2
Innovation and Top 1% Income Share - Full sample

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Top1%	Top1%	Top1%	Top1%	Top1%
Measure of Innovation	Patents	Cit5	Claims	Generality	Family
Innovation	-0.110***	-0.0443***	-0.0450***	-0.0456***	-0.0466***
	(-2.84)	(-2.91)	(-2.90)	(-2.83)	(-2.90)
Popgr	-0.0185	-0.0166	-0.0182	-0.0170	-0.0189
	(-1.63)	(-1.49)	(-1.57)	(-1.49)	(-1.64)
Gvtsize	-2.117***	-2.252***	-2.214***	-2.238***	-2.188***
	(-4.41)	(-4.89)	(-4.78)	(-4.85)	(-4.68)
Unemployment	1.352***	1.228***	1.295***	1.253***	1.222***
	(3.39)	(3.30)	(3.38)	(3.35)	(3.27)
Gdppc	0.544***	0.482***	0.486***	0.463***	0.480***
	(3.61)	(3.78)	(3.81)	(3.77)	(3.77)
Finance	-0.00105	0.0138	0.00765	0.00985	0.00294
	(-0.04)	(0.51)	(0.29)	(0.37)	(0.11)
Observations	495	495	495	495	495
R^2	0.746	0.750	0.749	0.751	0.748
F-first stage	32.86	34.99	39.79	41.04	38.65
Hansen p-value	0.4529	0.5453	0.5547	0.4056	0.5711
Groups	26	26	26	26	26

Notes: Innovation is taken in logs and lagged by one year. The dependent variable is the log of the top 1% income share. Panel data 2SLS regressions with country and year fixed effects. Time span: 1979-2012. The lag between the spillover instrument and the endogenous variables is set to 1 and the lead between the charges instrument and the endogenous variables is set to 3 years. Autocorrelation and heteroskedasticity robust standard errors are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

TABLE S3

Share of patents for every country in Database 3

Code	Share	Code	Share
AR	0.03%	**JP**	17.91%
AU	0.73%	**KR**	2.48%
BR	0.11%	**LB**	0.00%
CA	1.37%	**MU**	0.00%
CH	3.91%	**MY**	0.03%
CN	1.24%	**NL**	3.58%
CO	0.01%	**NZ**	0.12%
DE	19.21%	**PT**	0.05%
DK	0.84%	**RU**	0.15%
ES	0.78%	**SE**	2.27%
FR	7.83%	**SG**	0.16%
GB	4.57%	**TR**	0.13%
IE	0.27%	**US**	28.61%
IN	0.24%	**ZA**	0.11%
IT	3.27%		

Notes: LB has 49 patents and MU has 137 patents. Patents have been allocated based on their applicants. Time Period: 1978-2015

TABLE S4
Measures of Innovation and Top 1% Income Share allocation by applicants

	(1)	(2)	(3)	(4)	(5)
Dependent Variable	Top1%	Top1%	Top1%	Top1%	Top1%
Measures of Innovation	Patents	Cit5	Claims	Generality	Family
Innovation	-0.0934***	-0.0428***	-0.0405***	-0.0443***	-0.0412***
	(-2.92)	(-2.81)	(-2.95)	(-2.90)	(-2.94)
Popgr	-0.0175	-0.0175	-0.0159	-0.0169	-0.0178
	(-1.36)	(-1.31)	(-1.24)	(-1.28)	(-1.39)
Gvtsize	-2.121***	-2.087***	-2.205***	-2.217***	-2.177***
	(-4.18)	(-3.91)	(-4.54)	(-4.54)	(-4.39)
Unemployment	1.520***	1.459***	1.450***	1.447***	1.398***
	(3.62)	(3.54)	(3.62)	(3.62)	(3.57)
Gdppc	0.494***	0.463***	0.437***	0.437***	0.440***
	(3.78)	(3.70)	(3.96)	(3.95)	(3.91)
Finance	-0.0170	-0.0103	-0.0135	-0.00845	-0.0178
	(-0.65)	(-0.39)	(-0.52)	(-0.32)	(-0.68)
Observations	493	493	493	493	493
R^2	0.739	0.732	0.744	0.743	0.740
F-first stage	41.08	29.91	49.09	43.89	46.86
Hansen p-value	0.9497	0.9841	0.9423	0.8367	0.9538
Groups	26	26	26	26	26

Notes: Innovation is taken in logs and lagged by one year. The dependent variable is the log of the top 1% income share. Panel data 2SLS regressions with country and year fixed effects. Time span: 1979-2012. The lag between the spillover instrument and the endogenous variables is set to 1 and the lead between the charges instrument and the endogenous variables is set to 3 years. Autocorrelation and heteroskedasticity robust standard errors are presented in parentheses. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.