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Innovation and Inequality: some new evidences

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Abstract

In this project we use cross-country panel data to explore the relationship of patenting on income inequality. We find positive and significant correlation between innovation and top income inequality. We use several measures of innovation like the number of patents, proxies for the number of patents and quality measures. We apply also different measures of income inequality for robustness. We confirm the existence of a creative destruction effect by using lags of our quality measures of innovation. Next we apply GMM method to treat endogeneity. Finally we interpret our results and formulate our concerns.

Keywords: top income, inequality, innovation, patenting, citations, government sector

Sections

1 Introduction

Income inequality increases the last decades. Many scientists search the reasons behind this upward trend. In this assignment we argue that one of the reasons which accounts for the upward trend of income inequality is the evolution of patenting.

Figure 1 provides data for top income share and patenting. We can see that both income share and patents increase. We indicate that the impact of innovations on top 1% income share becomes stronger after the implementation date. This is the reason why income inequality growths later than the patents. Figure 1 illustrates this effect. Figure 2 uses the log form of the number of citations which a patent received, within five years after the application date and the log form of top 1% income share. Number of citations is a quality measure of innovation. The graph presents the difference between two distinct years for innovation and top income inequality. The positive correlation is clear.

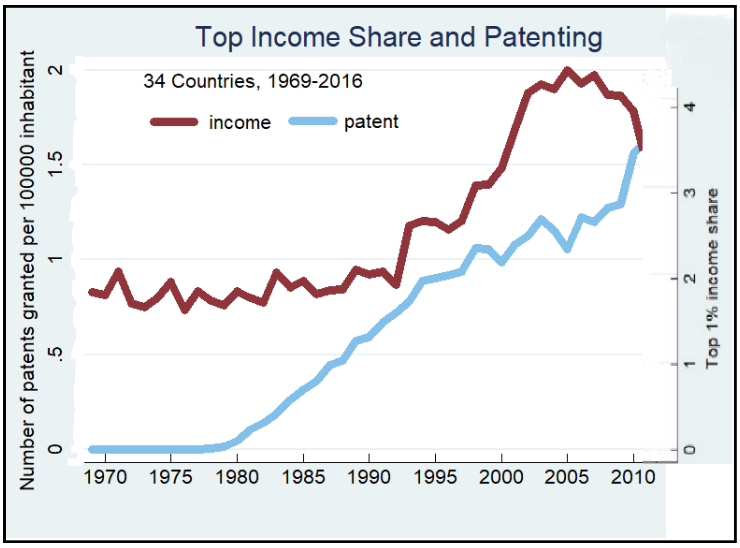

Figure 1: This figure illustrates the number of patents granted per 100000 inhabitants against the top 1% income share for the countries as a whole. Observations span the years 1969-2010.

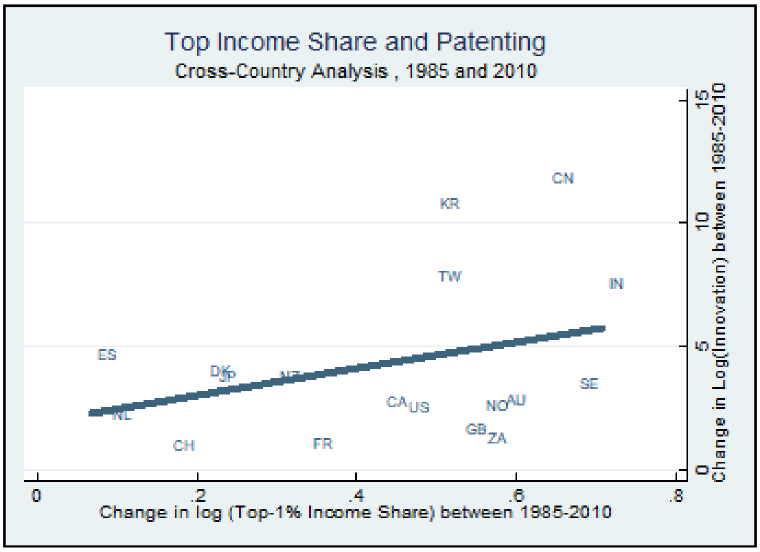

Figure 2: This figure illustrates the difference of the log of the number of citations per capita on a five year window against the difference of the log of the top 1% income share in 1985-2010. Observations are computed at the country level.

Our empirical analysis explores the effect of innovation on top income shares and other measures of inequality. First we apply OLS regressions to test the impact of innovation. Our findings indicate that innovation has a positive correlation with 1% top income share. We introduce the same quality measures of innovation like Aghion, Akcigit, Bergeaud, Blundell and Hemous (Innovation and Top Income Inequality, 2016). Our quality measures capture the positive effect of innovation. In contrast we find that innovation has no effect on overall inequality or to other top income shares except the 1%. Then we test the assumption of creative destruction by introducing older lags of quality measures of innovation to our model. The evidence show that the effect of innovation is not permanent and after 4 years the effect disappears. Our results survive from several robustness tests.

Next we address for endogeneity problem. We apply Generalized Method of Moments (GMM) by using lags of our variables as instruments. The GMM method confirms the OLS results and in addition improves our basic model. Again we use different measures of inequality for robustness checks.

We contribute to the existing literature of growth and inequality by testing the effect of innovation on top income inequality on country level. Our sample of countries is in table 1A and there are also descriptive statistics by country in table 1B. We use many different measures for the number of patents and for the quality of patents. In addition we test the effect of creative destruction.

Our model captures the effect of government sector on top income inequality which is our second contribution. Our OLS results support that the expansion of government sector reduces the top income shares and overall income inequality while GMM results confirm for only the top 1% income share.

The remaining part of the project is organized as follows. Section 2 includes a short literature review and provides also the expected results from the regressions. Section 3 describes the data, the construction of the indexes and the estimation strategy. Section 4 presents the results from OLS regressions and GMM. Section 5 concludes.

2 Expected Outcomes

We focus our research on innovation and top income inequality. However the measure of innovation is not the only control variable which we use. We control also for the GDP per capita, unemployment rate, population growth, government size and the financial sector. We examine their relationship with top income shares and Gini indexes. In this section we make a summary of the existing literature about inequality and we state the expected outcomes.

2.1 Innovation

There is an enormous increase in top income inequality in developed countries the past decades (Aghion, Akcigit, Bergeaud, Blundell, Hemous, 2016). We believe that one factor which drives the inequality upward is the innovation. Many models, of creative destruction, show that incumbents who innovate increase their market shares and erect barriers. According to AABBH[1] (2016) innovation from both incumbents and entrants increases top income inequality. Incumbents erect barriers which reduce the positive impact of innovation from new entrants.

A second mechanism which justifies the trend of inequality is the increase of capital gains (Aghion, Akcigit, Bergeaud, Blundell, Hemous, 2016). They state that the profits of the companies increased the past forty years when at the same time labor shares decreased. They indicate that an innovation causes productivity to growth and this fact leads to an increase in the relative shares of net entrepreneurial income over labor income. The source of the capital gains for the companies is the mark-up. Innovative companies can establish a bigger mark-up. Their results survive from many robustness tests. They use the number of patents and quality measures of innovation. They apply OLS and IV regressions of innovation on top income inequality.

Acemoglou shows in his paper “Why do new technologies complement skills? Directed technical change and wage inequality” that human capital has an important role on wage inequality. He states that the supply of college students increased the past decades. When there are more skilled workers, the market for technologies that complement skills is larger (Acemoglou, 1998). The more skilled workers earn bigger salaries and as a result wage inequality increases.

On European region level Lee (2011) indicates that there is a positive relationship between innovation and income inequality. However the author’s dataset of regions is for six years and uses as measure of innovation the number of patents. Number of patents is not as good measure of innovation as qualities measures are. Also as a dependent variable, Lee uses Gini coefficient. In the end author states that the results are sensitive. A second study of Lee and Rodrıguez-Pose (2012) supports that there is a positive effect of innovation on European region level but it has not clear effect on US cities. Again they use patents per capita as a measure of innovation and Gini index as

[1] AABBH: Aghion, Akcigit, Bergeaud, Blundell and Hemous.

dependent variable. They conclude that the effect of innovation for US is not the same between sectors.

Breau, Kogler and Bolton (2014) test the effect of innovation on Canadian cities. They use a dataset from 1996 to 2006. They apply Gini and Theil indexes as depended variables and number of patents as an explanatory variable. They find a positive effect between innovation and income inequality.

However Antonelli and Gehringer (2013) suggest that new technology can reduce income inequality. They propose a different mechanism. Technical change increases labor productivity which increases savings and investments. The reduction of interest rates leads to better wages and smaller wealth. They use Gini index as depended variable and patent applications from WIPO as control variable. They found that innovation has a negative effect on income distribution.

We expect a positive relationship of innovation on top income shares. In contrast some articles suggest that innovation has a positive impact on overall inequality while other articles suggest a negative impact or no effect at all.

2.2 GDP per capita

The majority of the papers test the effect of income inequality on economic growth and not the opposite. Theory states that equality has a positive impact on economic development (Perotti, 1992). The empirical results are not robust because economic crises have implications for the income inequality (Binatli, 2011).

In contrast Barro (2008) provides robust results of how GDP per capita affects income inequality. In his first paper states that there is a small effect of income inequality on growth rates (Barro, 2000). As measures of inequality he uses Gini indexes. Also inequality reduces growth in poor countries and boosts development in richer countries (Barro, 2000). However in his second paper he applies a different model (Barro, 2008). The results reveal a positive and significant relationship between GDP per capita and measures of inequality when the measures are used as dependent variables. GDP per capita has a positive effect on the overall Gini index and on highest quintile income shares (Barro, 2008). As a result we expect a positive sign for GDP per capita when we use Gini indexes as dependent variables or the top income shares.

2.3 Unemployment Rate

Many studies argue that unemployment rate has a significant effect on income inequality. Unemployment has a small effect for the bottom 20%, a negative effect for the bottom 50% and it seems to have a positive effect on top deciles (Nolan, 1985). However Nolan's sample is based on families and households and it has not take in consideration differences in the size and the composition of units.

A more recent research of Mocan (1998) tests the effect of structural unemployment and cyclical unemployment on different quintiles. She uses three different panels and her findings are very interesting. Structural unemployment appears to have a positive impact on the highest quintile in all the regressions (Mocan, 1998). In contrast it has a negative effect on bottom three quintiles. Cyclical unemployment seems to have the same signs with the structural but the results are not robust.

The rest of the literature between unemployment and inequality continues to support these findings. The unemployment preserves the negative effect on low quintiles and the positive effect on high quintiles (Jäntti, 1994). Jäntti shows that unemployment has a very strong negative impact on lower income groups, a small impact on median income groups and a very strong positive impact on top income group.

Recent research shows that income inequality increases over the last decades. The deterioration of the bottom quintile continues (Rao, 2015). According to Rao economic crisis boosts the inequality and the unemployment.

We expect a positive sign of unemployment on top income shares. When we use Gini indexes as depended variable we cannot be sure for the sign of the coefficient. If the impact of low quintiles is stronger, the coefficient is going to have a negative sign. In contrast if the impact of top income shares is stronger then it will have a positive sign but the magnitude is going to be smaller than on top income shares. So we expect a smaller magnitude or a negative one.

2.4 Population Growth

At this section we analyze how population growth affects inequality. Researchers focus on fertility rates and their impact on the distribution of income. The structure of the age distribution affects the current distribution of income due to the life cycle of earnings. The channels which population growth affects the income inequality are the mortality and fertility rates (Repetto, 1978). According to Repetto high fertility is associated with lower wages relative to returns on human and physical capital. The higher relative returns to capital are going to increase inequality. So fertility rate has a positive impact on income inequality.

In contrast with Repetto's findings Flegg (1979) argue that Gini index is not a good measure of income inequality while Atkinson's index is a more appropriate measure. The second author states that inequality can affect saving rate or the participation of women in labor force and to produce an indirect effect on fertility rate.

However more recent papers show that inequality has no impact on fertility rate (Boulier, 1982). Boulier suggests that using GDP per capita as an explanatory variable was a mistake because introduces a spurious nonlinearity into the model. It is seems like less inequality tends to reduce population growth and not the opposite (Rodgers, 1983). Rodgers' results from OLS indicate that there is a negative impact of population growth on income inequality. Although his results appear to be significant they did not survive from the Monte Carlo test and as a result they cannot be robust.

It is logical to expect a positive sign for population growth on top income shares because the top income shares are based on capital income. In addition it is possible population growth to have a small impact on Gini indexes or no impact at all.

2.5 Government Size

Usually median voter determines the government size and the distribution of income. There is a positive relationship between the mean income relative to the income of the decisive voter and the size of the government (Meltzer, Richard, 1981). Meltzer and Richard argue in their paper that the government size does not depend from the tax system or the bureaucracy. We can conclude that if the income of the median voter for a country does not belong to the top income shares, which is the most common fact, then the median voter is going to ask for redistribution. Top income shares are going to decrease after redistribution so we expect a negative sign for the government size. Big government size means big redistribution and less income inequality. In fact there is a research of the effect of government size on top 1% income share. Luo, Pickering and Monteiro (2017) use the same top 1% income share with us from the World Wealth and

Income Database. Their results from the panel regression with fixed effects and the IV regression confirm the negative relationship which we expect (Luo, Pickering, Monteiro, 2017).

There is another one explanation for the government size and the income inequality. Market imperfections can reduce income redistribution (Mello, Tiongson, 2006). They argue that there is negative correlation between income inequality and government spending in contrast with Meltzer and Richard. Their results for the lowest quintile of the distribution are robust and survive from OLS regressions and the IV regression. In the IV regression they use also instruments for the capital market.

To conclude we expect definitely a negative effect of government size on top income shares. For the other measures of income inequality the theory states that we should expect a positive effect of government size but the empirical literature so far gives a robust negative effect based on market imperfections.

2.6 Financial Sector

Financial sector is an important variable to our model. It captures the evolution of the top wages. Financial sector was a high wage industry (Philippon, Reshef, 2012). We expect a big proportion of employees with top incomes to be part of the financial sector (Aghion, Akcigit, Bergeaud, Blundell, Hemous, 2016).

The expansion of financial sector affects the productivity and the income shares of workers and capitalist (Panico, Pinto, Anyul, 2012). Palma (2009) argues that the top 1% income share has many fluctuations from 1913 to 2006. The results are robust even when we include the capital gains. Also the bottom 90% of income share seems unaffected from the financial sector. We focus on the period from 1980 to 2013. It is the period which we have data for the quality measures of the patents. However the development of new technologies after the 1970 increases the power of financial sector and makes its relationship with income inequality more robust (Panico, Pinto, Anyul, 2012). Financial sector gradual increases top income inequality after 1970 (Palma, 2009).

In addition income inequality is not the only measure which increased after 1970. According to Panico and Pinto (2015), the profits of the companies and financial innovation also increased. In recent years banking sector made adjustments in financial regulations. The profit of the financial industry increases more than other sectors of the economy and this situation benefits the managers, shareholders and workers of large companies (Panico, Pinto, 2015). Top income inequality increases at the same time.

Szymborska (2016) tests the effect of financial sector on top 10% of income distribution. The author applies OLS and GMM method but the results are not very robust. She uses three different proxies for financial sector but only one of the measures gives the positive sign in both regression methods as we expect from the theory.

We expect a positive sign for financial sector on top income shares. In addition we don't think that financial sector is going to have a strong effect on total inequality because it captures only capital gains.

3 The empirical framework

In this section we present the measures of inequality and the data which we used to compute them. Our methodology is similar to Philippe Aghion, Ufuk Akcigit, Antonin Bergeaud, Richard Blundell and David Hemous (2016).

3.1 Data and Measurement

Our purpose is to test the relationship between innovation and top income inequality on country level. We confront several problems with the validity of the data. This is the reason why we don't keep the amount of observations steady among different tables. Instead we manage to keep steady the amount of observations between different regressions at the same table. We apply this estimation strategy because we don't want to exclude observations from the sample. Our dataset for the number of patents starts in 1962 and for the quality measures of patents in 1978.

3.1.1 Inequality

The data on the share of income owned by the top 1% and the top 10% of the income distribution for our country panel analysis are drawn from the World Wealth and Income Database (Alvaredo, Atkinson, Chancel, Piketty, Saez, Zucman, updated in 2017). These data are available for some countries from 1870 to 2016 but we focus on the period after

1960. We prefer the Standardized World Income Inequality Database (Frederick Solt, updated in 2016) for the Gini indexes. The Standardized World Income Inequality Database provides us 100 equivalent Gini indexes for the pre-tax income. Every Gini index has a different standard deviation. We include to our analysis two Gini indexes, the one with the smallest standard deviation and the one with the biggest standard deviation. This method allows us to have a good signal for the distribution of the Gini indexes. Again we include data only after 1960. In the end we have an unbalanced panel of 34 countries over a maximum time period of 54 years for the number of patents and 34 years for the quality measures of patents. The only country from the above sample that cannot participate in any regression is Taiwan. There are data for Taiwan for both inequality and measures of patents but there aren't any data for the additional control variables.

The World Wealth and Income Database provides us the top 1% share and the top 10% share of pre-tax national income. The pre-tax labor income and the pre-tax capital income compose the pre-tax national income (Alvaredo, Atkinson, Chancel, Piketty, Saez, Zucman, 2017). Also we prefer pre-tax national over the pre-tax factor income because the first one is less affected by the age structure of the population (Alvaredo, Atkinson, Chancel, Piketty, Saez, Zucman, 2017). It is crucial the existence of capital income in the composition of pre-tax national income because firm owners, inventors and top managers are the categories of people which earn most of the benefits from innovation (Aghion, Akcigit, Bergeaud, Blundell, Hemous, 2016).

3.1.2 Patents

We gather data for innovation from two separate sources. We use five different variables in order to find a good measure of the number of patents for every country. Wipo provides us the number of patents which granted between the years 1982 and 2015. Also, it gives us the number of applications filled between the years 1982 and 2015 for the patent families and between the years 1962 and 2015 for residents and no residents. We use the number of applications as a proxy for the number of patents. The problem is that the number of applications is biased because many applications are not granted in the end. In addition we want to include quality measures of innovation for our research.

OECD gives us three different databases: the Triadic Patent Families database, the Citations database, and the Measuring Patent Quality database. The databases have vital contribution to our research. First the Triadic Patent Families database provides us data for the number of patents per family from 1968 to 2015. We exclude from the database the patents which are not granted. Then we have to confront two serious problems. The first one is that there are many different inventors from different countries for the same patent family. We make the same assumption with Aghion, Akcigit, Bergeaud, Blundell and Hermous (2016) that the patents are equally split among the inventors. This assumption allows us to construct weights for every inventor and to split the patents among different countries. The second problem is that we have three different dates for every patent family. The reason for this is that many patents which belong to the same family have been created in different time periods. The database provides us the number of patents per family for each different time period and this allows us to create a second group of weights this time based on different years. After we split the patents between the inventors we split them again between the different time periods which have been granted. We assume also like Aghion, Bergeaud, Blundell and Hermous (2016) that the locations of the inventors are the same with the locations of the companies. All the measures of the number of patents have been divided by population and been taken in log.

The Citation database and the Measuring Patent Quality database provide data for the quality of patents. In details we extract data for patent citation, the number of claims in a patent and the generality index. We follow the same methodology like Aghion, Bergeaud, Blundell and Hermous (2016) and we manage to construct the same quality measures. We have the measure of 5-year window citations counter, Patent breadth and Generality index like them. In addition we have the data to create the measures of 3-year window citations counter and 7-year window citations counter. Patent breadth defined as the number of claims in a patent and the generality index is based on the definition of Hall (2001). The citation counters count the number of citations which a patent receive in a three year window, five and seven respectively. Except from these quality measures which Aghion, Bergeaud, Blundell and Hermous use in their paper we apply another one measure of inequality. The name of this measure is Grant lag and is based on the time elapsed between the filing date of the application and the date of the grant. The grant lag index is higher when the decision to grant has been taken very fast and lower when the decision to grant has been taken very slow (Squicciarini, M., H. Dernis and C. Criscuolo, 2013). All the quality measures have been aggregated at the country level and then divided first by population and second by the weighted number of patents. Also we took the log form of all these measures.

3.1.3 Control Variables

We add the rest of the control variables by following the model of Philippe Aghion, Ufuk Akcigit, Antonin Bergeaud, Richard Blundell and David Hemous (Innovation and top income inequality, 2016). All the other control variables are from World Bank from 1960 to 2016. We control for the financial sector by using the domestic credit provided by financial sector as a percentage of GDP as a proxy and for the government sector by using general government final consumption expenditure as a percentage of GDP as a proxy. We also include controls as GDP per capita and population growth. Like Aghion, Akcigit, Bergeaud, Blundell and Hemous in their paper we control for the business cycle via unemployment rate. We prefer the variable unemployment national estimate over the variable unemployment ilo estimate because the first one has more observations. We use also GDP growth in some regressions tables. Additional information, about the number of countries or the years, exists in the notes under every regression table.

3.2 Estimation Strategy

We want to examine the relationship and the magnitude of the number of patents and the quality measures of innovation on top income shares. First we test them on 1% income share and estimated equation is:

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

where i is a vector for a country, t is a vector for a time period, y_{it} is the measure of inequality (in log), A is the constant, B_i is a country fixed effect, B_t is a year fixed effect, $\left(innov_{i(t-1)}\right) + b_2$ is innovation in year $t-1$ (also in log) , X the other control variables and ε_{it} the disturbing term. We use year and country fixed effects to vanish permanent cross state differences in inequality and also aggregate changes in inequality. The advantage by taking both the measure of inequality and the measure of innovation in logs is that b_1 can be interpreted as the elasticity of inequality with respect to innovation.

We decide to take the one year lag of innovation as independent variable because according to table 3 the biggest impact of a patent takes place then. We use as a quality measure of innovation the citations which a patent received in a three year window. The first year after the patent being granted the magnitude of the coefficient is the biggest and it is statically significant. We apply autocorrelation and heteroskedasticity robust standard erros using the Newey-West variance estimator in all our regressions.

4 Results from OLS and GMM Regressions

In this section we present the results from OLS and GMM regressions of top income shares and other measures of inequality on innovation. We examine the correlation between innovation and top income inequality. After that we test the relationship between the measures of innovation and different measures of inequality. Our final tables from OLS regressions are for different lags of innovation and their magnitudes on top 1% of income share. We use GMM method to tackle the endogeneity problem. Again we apply this method on different measures of both innovation and inequality. There are the definitions of all the variables which we use for OLS regressions and GMM regressions in table 2A. Also there are summary statistics for all the variables in table 2B.

4.1 Innovation and Top Income Inequality

The tables 4 to 13 are about different measures of innovation on top 1% income share. First we construct the basic model in table 4. We add the variables separate because we want to understand how the model changes. We begin with the citations which a patent received in a three year window and the share of financial sector as independent variables. The quality measure of innovation is significant and it has the sign expected from theory. In contrast the financial sector has a negative sign but not statically significant. Next we add population growth. Again it has the wrong sign but it is not significant and that is the reason why the coefficient of innovation doesn't change. Our next step is to add the government sector. Government sector is significant and it has the negative sign which we expect. The next columns are very crucial. First we have the effect of unemployment which is significant and with the correct sign. When we use the variable of unemployment, we reduce our sample but we improve our results. Unemployment boosts the impact of innovation and government size on top 1% income share. Then we have to add the last control variable of our model the GDP per capita. Here is the main problem of our research. It appears that when we add the GDP per capita on log form the measure of innovation loses its impact on income inequality. We a have a possible explanation. In contrast with Aghion P., Akcigit U., Bergeaud A., Blundell R. and Hemous D. (Innovation and top income inequality, 2016) we do not process data for our control variables, government sector and financial sector, as percentages of GDP per inhabitant. World Bank cannot provide us these variables. As a result the use of log form of GDP per capita introduces a more linear approach to our model which correlates with the measure of innovation. There is high correlation between the measure of innovation and log form of GDP per capita for many countries. This is the reason why we apply GDP per capita without the log form in column 6 and the GDP per capita growth as an alternative measure in column 7. Our basic model is in column 6.

We use different measures of the number of patents for tables 5, 6 and 7. We apply GDP per capita growth in table 6 for robustness. Also we present for only this time how the model collapses when we use GDP per capita on log form in table 7. Our basic model is in table 5. The only variable that has correct sign and is significant for all the columns as we expect from theory is the government size. Also unemployment has the positive effect which we expect but it is not significant after the first two columns. We use the number of patents as a measure of innovation for the first and the second column and number of applications for the rest of the columns. We know that applications are a bias measure of innovation because all applications are not being granted at the end. We use them only as proxies for the number of patents. We use the number of patents which we extract from the OECD database in the first column and the number of patents which WIPO provides in the second column. Both have a positive effect but they aren’t significant. The number of patents is not a good measure of innovation because a patent which has a big contribution and a patent with small contribution will have the same weight (Aghion, Akcigit, Bergeaud, Blundell, Hemous, 2016).

In contrast tables 8 to 13 provide quality measures of innovation as independent variables. We use GDP per capita growth in tables 9, 11 and 13 for robustness tests. From table 8 we can see that the quality measures of innovation have a positive and significant effect on top 1% income share. The first column uses the citations which a patent received in a three year window, the second column uses the time elapsed between the filing date of the application and the date of the grant, column 3 uses the generality weighted patent count and column 4 uses the number of claims. Again unemployment and government sector are significant and with the correct sign. Financial sector and population growth have wrong signs but at least they are not significant. Finally GDP per capita has the correct sign but it is not significant. We keep the amount of observations steady between the different quality measures of innovation. We took the log form for measures of innovation and for top income shares and we can interpret the coefficient of innovation as elasticity. A 1% increase in the number of citations is associated with a 0.0346% increase on top 1% income share. The variables of government sector and unemployment rate are in percentages. A 1% increase of government sector is associated with a 2.786% decrease on top 1% income share. Also a 1% increase of unemployment rate is associated with 1.201% increase on top 1% income share. The rest of the control variables are not significant.

We provide the tables 10 and 12 for robustness tests. Tables 10 and 12 have the same quality measures but in a five year window and a seven year window respectively. The effects of innovation, government sector and unemployment on top 1% income share remain and they are significant also.

4.2 Innovation and Other Measures of Inequality

We check the effect of innovation on Top 10% income share, on average top income share and on Gini index. Each of the tables 14 to 17 uses a different quality measure of innovation as an independent variable. We construct G99 measure of inequality by subtracting the 1% income share from Gini index (Aghion P., Akcigit U., Bergeaud A., Blundell R.,Hemous D., 2016). G99 includes all the income distribution except the 1% top income share. We derive average top income share by subtracting the 1% income share from the top 10% income and then we divide it by 9 (Aghion P., Akcigit U., Bergeaud A., Blundell R.,Hemous D., 2016). This measure represents the average share of income received by each percentile of the income distribution from top 10% to top 2%. World Wealth and Income Database doesn’t provide us data for Argentina, Colombia and Indonesia on top 10% income share. As a result we have to exclude them from our tables in order to keep the amount of observations steady among different measures of inequality.

In table 14 we provide the effect of citations on different measures of inequality. Instead of using all the variables of citations we apply only citations on a five year window because it is a measure between the three years window and the seven years window. The first column is the same as the previous tables. The only difference is that we exclude the three countries which we mention above from our sample. It is clear from the tables 14 to 17 that innovation has a positive and significant effect only on top 1% income share. We have a very robust effect of unemployment in all tables. We expect from theory that unemployment will have a positive and significant effect on top income shares but it seems to have the same effect for all the income distribution. It appears that the government sector has a negative impact on overall Gini index but after we subtract the 1% income top share from the whole income distribution the effect disappears. So we assume that our regression captures the effect of government sector on top 1% income share even when we use the overall income distribution. The variable which appears to be completely wrong is the financial sector. We expect a positive impact from theory on top 1% income share. The variable is not significant on top 1% income share and in addition it has a positive and significant effect on G99.

We provide tables 15, 16 and 17 for robustness tests. In these tables we apply different quality measures of innovation on income shares like claims, grant lag and generality index.

4.3 Top Income Inequality and Innovation at Different Time Lags

Next we check the effect of innovation on top 1% income share at different time lags. We test the theory of Schumpeterian models and their effects of creative destruction and imitation on top income shares (Aghion P., Akcigit U., Bergeaud A., Blundell R.,Hemous D., 2016). Tables 18 to 23 illustrate these effects. We use 6 lags of innovation for every regression table.

Tables 18, 19 and 20 use citations as quality measures of innovation. We have to reduce our sample on each table. The amount of observations depends on the measure of citations. In table 18 we apply citations which a patent received in a three year window so we have to restrict the time period from 1983 to 2013. We apply the same method for five year window in table 19, we restrict the time period from 1983 to 2011, and for seven year window in table 20, again we restrict the time period from 1983-2009). In table 18 the effect of innovation disappears after the fifth year. In contrast in tables 19 and table 20 the effect disappears after the fourth year. We select the table 19 as the basic model because the five year window is a measure between the three year and the seven year. Also it is safer to apply this measure because we know for sure that the calculation of citations have completed.

Tables 21, 22 and 23 are being used for robustness. Again every table uses a different quality measure of innovation. We restrict the amount of observations from 1983 to 2011 in order to be comparative with the results of table 19. All the tables illustrate that the effect of innovation disappears after the fourth year.

4.4 Endogeneity of Innovation and GMM Results

It is possible that top inequality affects also innovation. It is common for rich companies to create barriers in their sectors. They manage to discourage new entrants and as a result innovation is being reduced (Aghion P., Akcigit U., Bergeaud A., Blundell R.,Hemous D., 2016).

We control for endogeneity by using GMM method. We do not have the same instruments like Aghion P., Akcigit U., Bergeaud A., Blundell R. and Hemous D. on country level so we use lags of our variables as instruments. Also we introduce to our model as an independent variable the one year lag of the dependent variable. We believe that the inequality of the previous period affects the current inequality. Our new model is:

$$log(y_{it}) = b_1 log\left(innov_{i(t-1)}\right) + b_2 log(y_{i(t-1)}) + b_3 X_{it} + \varepsilon_{it} \quad (2)$$

where $y_{i(t-1)}$ is the lag of independent variable in log. The rest of control variables for the equation (2) are the same with the equation (1). We subtract from the equation the B_i which was the country fixed effects and the B_t which was the time fixed effects. The difference GMM uses first differences to transform the regressors. By transforming the regressors the fixed country-specific effect is removed (Mileva, 2007). In contrast with country fixed effects, the time fixed effects are being used to prevent contemporaneous correlation (Roodman, 2009). Usually the researchers apply GMM method on datasets with large N (observations) and small T (time periods). In our dataset the N is almost equal with T. Our model collapses, when we include time fixed effects, because we have too many instruments. So we apply GMM method without time fixed effects as a second best solution.

We use one to five lags of quality measure of innovation as instruments and two to five lags of income inequality as instruments. We do not use the first lag of income inequality as an instrument because we have it as an independent variable. Also we apply one to three lags for the rest of the independent variables as instruments to our model. We adopt a model like (Breau, Kogler and Bolton, 2014) by using the five year lags of innovation measure as instruments and by introducing the lag of the dependent variable as a regressor. We construct seven tables. Every table has a different measure of inequality as an independent variable.

Table 24 provides different measures of innovation on top 1% income share. Quality measures of innovation, government sector and unemployment have the correct signs and they are significant like OLS regressions. In addition we have two variables that are significant and with the correct sign. Financial sector has the positive impact which we expect from theory. Also the lag of inequality appears to have positive and significant effect on current inequality. Both the p-values of Sargan and Arellano-Bond test are big as a result we cannot reject the Ho hypothesis. The Ho hypothesis for Sargan test states that the instruments as a group are exogenous and for Arellano-Bond that there isn't autocorrelation in levels (Mileva, 2007).

We use top 10% income share as dependent variable in table 25. It is clear from the table that the effect of innovation disappears except from the first column. In addition the magnitude of citations is very small. We reach to the same conclusion with the OLS regressions that innovation affects only top 1% income share.

Tables 26 and 27 are very crucial because provide results for the income distribution after we exclude the top 1% income share. We can see that the effects of all our control variables disappear. We expect from theory that innovation, population growth and financial sector have no effect on income inequality and our results confirm that. Also lag of dependent variable has no effect on income inequality. Tables 28 and 29 are for Gini index and table 30 for average top.

5 Conclusion

In this project we examined the correlation between innovation and top income inequality. We found that quality measures of innovation have positive and significant effect on top 1% income share. In contrast with Aghion, Akcigit, Bergeaud, Blundell and Hemous we indicate that the size of government sector has a significant and negative impact on top 1% income share while unemployment has a significant and positive sign. One possible explanation is that many countries from our sample have a less flexible labor market than USA or a much bigger government sector. Our results survive from several robustness tests.

We have two major concerns. The first one is about the control variables. Aghion, Akcigit, Bergeaud, Blundell and Hemous have their control variables (Financial sector and Governemnt sector) as percentages of GDP per capita. In contrast we have them as percentages of GDP because World Bank cannot provide us the same control variables. Also we didn’t use the log form of GDP per capita. Our control variables government sector and GDP per capita are similar with Antonelli and Gehringer. They used also control variables as percentages of GDP.

Our second concern is about the GMM method. GMM method doesn’t fit well with our data because we have many years and our sample isn’t big enough. We apply GMM method because we couldn’t find the right instruments for IV regression.

In the future we hope to find better control variables because financial sector is important for our research. In addition we want to correct the endogeneity problem. As a result we have to search for right instruments because GMM is a temporary solution.

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Table 1A: Sample of Countries

Argentina	Malaysia
Australia	Mauritius
Brazil	Netherlands
Canada	New Zealand
China	Norway
Colombia	Portugal
Denmark	Russian Federation
Finland	Singapore
France	South Africa
Germany	Spain
India	Sweden
Indonesia	Switzerland
Ireland	Taiwan**
Italy	Turkey
Japan	United Kingdom
Korea*	United States
Lebanon	Zimbabwe

Notes: Number of countries 34. *we mean South Korea **Taiwan has data only for patents and income inequality, doesn’t participate in any regression.Time: 1960-2015.

Table 1B: Descriptive statistics by country in two distinctive years

Country	1985		2010	
	Innovation	**Top 1%**	**Innovation**	**Top 1%**
AU	0.0002387	0.0481	0.0038786	0.0859
CA	0.0003133	0.0888	0.0048286	0.1362325
CH	0.00088	0.09051	0.0022878	0.1062789
CN	1.82E-09	0.080038	0.000234	0.1512303
DK	0.0001118	0.052123	0.0058947	0.0641461
ES	1.21E-06	0.08119	0.0001213	0.08687
FR	0.0006626	0.077374	0.0018049	0.108437
GB	0.0015063	0.074	0.0072424	0.1255
IN	5.13E-09	0.104524	9.53E-06	0.2121685
JP	0.0005606	0.08383	0.0233413	0.10439
KR	1.46E-07	0.071577	0.0066792	0.1175936
NL	0.0001389	0.0592	0.0011947	0.064481
NO	0.0001238	0.044497	0.0016139	0.0774196
NZ	0.0000356	0.055097	0.0014689	0.07402
SE	0.0002815	0.0459	0.0085879	0.0898375
TW	8.79E-07	0.068383	0.0022187	0.1119875
US	0.0016601	0.12553	0.0204732	0.198
ZA	9.91E-06	0.1064	0.0000332	0.1854127

Notes: Number of citations within a five-year window per capita and top 1% income share for 18 countries 1985 and 2010.

Table 2A: VARIABLE DESCRIPTION AND NOTATION

Variable names	Description
	Measures of inequality
Top 1%	Share of income own by the richest 1%, WID.
Top 10%	Share of income own by the richest 10%, WID.
Avgtop	Average income share for the percentiles 10 to 2 in the income distribution.
Gini (S)	Gini index of inequality with small standard deviation, SWIID.
Gini (L)	Gini index of inequality with big standard deviation, SWIID.
G99 (S)	Gini index restricted to the bottom 99% of income distribution with small standard deviation.
G99 (L)	Gini index restricted to the bottom 99% of income distribution with big standard deviation.
	Measures of innovation
Patent (W)	Weighted number of patents granted by the USPTO, EPO and JPO per inhabitants, OECD.
Patent	Total patent grants (direct and PCT national phase entries) by filing office, WIPO.
Nonresident (A)	Nonresident filings through the Patent Cooperation Treaty procedure or with a national patent office, World Bank.
Resident (A)	Resident filings through the Patent Cooperation Treaty procedure or with a national patent office, World Bank.
Patent family (A)	Patent family applications by origin and first filing office, WIPO.
Cit3	Total number of citation received no longer than 3 years after applications per inhabitant, OECD.
Cit5	Total number of citation received no longer than 5 years after applications per inhabitant, OECD.
Cit7	Total number of citation received no longer than 7 years after applications per inhabitant, OECD.
Grant lag	The time elapsed between the filing date of the application and the date of the grant, OECD.
Generality	Total number of patents weighted by the generality index per inhabitants, OECD.
Claims	Total number of claims associated with patents per inhabitants, OECD.
	Control variables
Gdppc	Real GDP per capita in US $, World Bank.
LGdppc	Real GDP per capita in US $ (in log), World Bank.
Gdppcgr	Real GDP per capita growth in US $, World Bank.
Popgrowth	Growth of total population, World Bank.
Sharefinance	Domestic credit provided by financial sector (% of GDP), World Bank.
Unemployment	Unemployment, total (% of total labor force) (national estimate), World Bank.
Gvtsize	General government final consumption expenditure (% of GDP), World Bank.
	Additional control variables for the GMM regressions
L.Top1	Share of income own by the richest 1% lagged by one year, WID.
L.Avgtop	Average income share for the percentiles 10 to 2 in the income distribution lagged by one year, WID.
L.Top10	Share of income own by the richest 10% lagged by one year.
L.G99(S)	Gini index restricted to the bottom 99% of income distribution with small standard deviation lagged by one year.
L.G99(L)	Gini index restricted to the bottom 99% of income distribution with big standard deviation lagged by one year.
L.Gini(S)	Gini index of inequality with small standard deviation lagged by one year, SWIID.
L.Gini(L)	Gini index of inequality with big standard deviation lagged by one year, SWIID.

Notes: Description of relevant variables used in the next tables regressions.

Table 2B: SYMMARY STATISTICS

Variable	Obs.	Mean	Std. Dev.
Measures of Inequality			
Top 1%	1251	-2.37012	0.41632
Top 10%	1071	-1.12056	0.216415
Avgtop	1066	-3.65454	0.172329
Gini (S)	1470	-0.80394	0.154041
Gini (L)	1470	-0.80972	0.178635
G99 (S)	1038	-0.96747	0.170211
G99 (L)	1038	-0.97128	0.202777
Measures of Innovation			
Patent (W)	1203	-12.3976	3.109935
Patent	1042	-9.13115	1.787809
Nonresident (A)	1553	-8.98822	1.751551
Resident (A)	1538	-9.48211	2.124426
Patent family (A)	1102	-9.95421	2.548471
Cit3	1051	-16.0739	2.201773
Cit5	1051	-14.6055	2.238928
Cit7	1051	-14.3211	2.274248
Grant lag	1051	-8.66339	2.163807
Generality	1051	-17.331	2.039663
Claims	1051	-13.6382	2.074873
Control Variables			
Gdppc	1751	0.216964	0.188449
LGdppc	1802	9.47973	1.272853
Gdpcgr	1718	0.026039	0.040665
Popgrowth	1931	1.098411	0.916825
Sharefinance	1707	0.884702	0.596904
Unemployment	1317	0.066852	0.043656
Gvtsize	1801	0.161612	0.048299

Notes: We don't provide summary statistics for the lags of the variables.

Table 3: LAGS OF INNOVATION

Dependent variable	Top 1% Income Share						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Lag of innovation	no	1 year	2 years	3 years	4 years	5 years	6 years
Cit3	0.0225*						
	(1.69)						
Cit3		0.0260*					
		(1.80)					
Cit3			0.0241*				
			(1.77)				
Cit3				0.0199			
				(1.43)			
Cit3					0.0178		
					(1.30)		
Cit3						0.0107	
						(0.79)	
Cit3							0.00972
							(0.76)
R^2	0.9097	0.9131	0.9174	0.9187	0.9205	0.9194	0.9196
Observations	791	770	747	726	698	676	651

Notes: Number of countries: 33 for columns (1, 2, 3, 4, 5, 6, 7). Time span: 1977-2013 for column (1), 1978-2013 for column (2), 1978-2013 for column (3), 1979-2013 for column (4), 1980-2013 for column (5), 1981-2013 for column (6), 1982-2013 for column (7).
Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***,** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 4: CONSTRUCTION OF THE MODEL

Dependent variable	Top 1% Income Share						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Cit3	0.0307**	0.0307**	0.0290*	0.0325**	0.0127	0.0346**	0.0307**
	(1.97)	(1.98)	(1.91)	(2.29)	(0.66)	(2.38)	(2.21)
Sharefinance	-0.0978	-0.0973	-0.0801	-0.0511	-0.0364	-0.0648	-0.0277
	(-1.62)	(-1.64)	(-1.35)	(-0.98)	(-0.72)	(-1.15)	(-0.56)
Popgrowth		-0.00603	-0.0150	0.0121	0.0227	-0.00122	0.0244
		(-0.33)	(-0.90)	(0.55)	(0.90)	(-0.06)	(1.08)
Gvtsize			-2.273*	-2.971***	-2.774**	-2.786**	-2.431**
			(-1.94)	(-2.63)	(-2.51)	(-2.43)	(-2.11)
Unemployment				0.953**	1.188**	1.201**	1.013**
				(2.05)	(2.30)	(2.38)	(2.27)
LGdppc					0.182*		
					(1.74)		
Gdppc						0.796	
						(1.36)	
Gdppcgr							0.895**
							(2.36)
R^2	0.9196	0.9198	0.9233	0.9287	0.9309	0.9311	0.9305
Observations	716	715	715	676	676	676	676

Number of countries: 32 for columns (1, 2, 3) and 31 for columns (4, 5, 6, 7). Time span: 1977-2013 for all columns.
Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***,** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 5: TOP 1% INCOME SHARE AND INNOVATION

Dependent Variable	Top 1% Income Share				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Measure of Innovation	Patent (W)	Patent	Nonresident (A)	Resident (A)	Patent family (A)
Innovation	0.00950	0.0226	0.0165	-0.0336*	0.00383
	(0.52)	(1.35)	(0.73)	(-1.67)	(0.17)
Gdppc	0.647	0.869	0.352	0.404	0.930
	(1.05)	(1.47)	(0.72)	(0.88)	(1.60)
Popgrowth	0.00617	0.0182	0.0104	-0.00942	-0.00435
	(0.21)	(1.02)	(0.39)	(-0.52)	(-0.18)
Gvtsize	-2.926***	-2.223**	-2.756**	-3.217***	-1.903*
	(-2.68)	(-2.15)	(-2.53)	(-3.47)	(-1.78)
Unemployment	1.082*	1.075*	0.626	0.631	0.972
	(1.79)	(1.74)	(1.09)	(1.18)	(1.56)
Sharefinance	-0.000954	-0.0122	0.00944	-0.00570	-0.00901
	(-0.01)	(-0.19)	(0.16)	(-0.11)	(-0.14)
R^2	0.9208	0.9288	0.9132	0.9142	0.9257
Observations	762	683	820	817	704

Notes: The table presents estimates of equivalent measures of innovation on the top 1% income share of country income. I consider different measures of the number of patents which are all lagged by 1 year and standardized by country population: column (1) uses the number of patents weighted by their inventors, column (2) uses the number of patents, column (3) uses the number of non residents' applications, column (4) uses the number of residents' application and column (5) uses the number of applications by patent family. Number of countries: 33 for column (5), 32 for columns (1, 3, 4) and 31 for column (2). Time span: 1968-2015 for column (1), 1982-2015 for column (2, 5) and 1962-2015 for columns (3, 4).

Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***,** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 6: TOP 1% INCOME SHARE AND INNOVATION

Dependent variable	Top 1% Income Share				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Measure of innovation	Patents (W)	Patents	Non residents (A)	Residents (A)	Patent family
Innovation	0.0109	0.0175	0.0191	-0.0305	0.00185
	(0.66)	(1.12)	(0.83)	(-1.62)	(0.09)
Gdppcgr	0.694*	1.031**	0.629*	0.446	0.729
	(1.71)	(2.35)	(1.78)	(1.23)	(1.56)
Popgrowth	0.0257	0.0385	0.0243	0.00291	0.0204
	(0.73)	(1.61)	(0.77)	(0.14)	(0.64)
Gvtsize	-2.673**	-1.837*	-2.408**	-2.990***	-1.724
	(-2.53)	(-1.79)	(-2.11)	(-3.18)	(-1.64)
Unemployment	0.906*	0.824	0.486	0.478	0.741
	(1.66)	(1.48)	(0.92)	(0.98)	(1.28)
Sharefinance	0.0273	0.0226	0.0245	0.00598	0.0259
	(0.46)	(0.40)	(0.45)	(0.11)	(0.45)
R^2	0.9203	0.9281	0.9134	0.9137	0.9235
Observations	762	683	819	816	704

Notes: The table presents estimates of equivalent measures of innovation on the top 1% income share of country income. I consider different measures of the number of patents which are all lagged by 1 year and standardized by country population: column (1) uses the number of patents weighted by their inventors, column (2) uses the number of patents, column (3) uses the number of non residents' applications, column (4) uses the number of residents' application and column (5) uses the number of applications by patent family. Number of countries: 33 for column (5), 32 for columns (1, 3, 4) and 31 for column (2). Time span: 1968-2015 for column (1), 1982-2015 for column (2, 5) and 1962-2015 for columns (3,4).

Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***,** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 7: TOP 1% INCOME SHARE AND INNOVATION

Dependent variable	Top 1% Income Share				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Measure of innovation	Patents (W)	Patents	Non residents (A)	Residents (A)	Patent family (A)
Innovation	-0.00676	-0.000324	0.0148	-0.106***	-0.0255
	(-0.35)	(-0.02)	(0.64)	(-4.79)	(-1.16)
LGdppc	0.138**	0.144*	0.0271	0.389***	0.196***
	(2.22)	(1.79)	(0.36)	(4.62)	(2.74)
Popgrowth	0.0224	0.0318	0.0173	-0.00201	0.0165
	(0.63)	(1.33)	(0.55)	(-0.13)	(0.58)
Gvtsize	-2.785***	-2.303**	-2.764**	-3.262***	-1.994**
	(-2.77)	(-2.39)	(-2.49)	(-3.71)	(-1.97)
Unemployment	1.040*	1.031*	0.531	0.981**	1.015*
	(1.84)	(1.71)	(0.96)	(2.10)	(1.70)
Sharefinance	0.0159	0.00138	0.0118	0.00202	0.00847
	(0.27)	(0.02)	(0.21)	(0.05)	(0.15)
R^2	0.9205	0.9272	0.9125	0.9209	0.9252
Observations	762	683	820	817	704

Notes: The table presents estimates of equivalent measures of innovation on the top 1% income share of country income. I consider different measures of the number of patents which are all lagged by 1 year and standardized by country population: column (1) uses the number of patents weighted by their inventors, column (2) uses the number of patents, column (3) uses the number of non residents' applications, column (4) uses the number of residents' application and column (5) uses the number of applications by patent family. Number of countries: 33 for column (5), 32 for columns (1, 3, 4) and 31 for column (2). Time span: 1968-2015 for column (1), 1982-2015 for column (2, 5) and 1962-2015 for columns (3,4).

Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***,** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 8: TOP 1% INCOME SHARE AND INNOVATION

Dependent variable	Top 1% Income Share			
	(1)	**(2)**	**(3)**	**(4)**
Measure of innovation	Cit3	Grant lag	Generality	Claims
Innovation	0.0346**	0.0377**	0.0422**	0.0387**
	(2.38)	(2.32)	(2.05)	(2.32)
Sharefinance	-0.0648	-0.0646	-0.0702	-0.0686
	(-1.15)	(-1.13)	(-1.24)	(-1.20)
Popgrowth	-0.00122	-0.00146	-0.000292	0.000304
	(-0.06)	(-0.08)	(-0.01)	(0.02)
Gvtsize	-2.786**	-2.801**	-2.766**	-2.799**
	(-2.43)	(-2.51)	(-2.43)	(-2.51)
Unemployment	1.201**	1.236**	1.207**	1.220**
	(2.38)	(2.40)	(2.43)	(2.39)
Gdppc	0.796	0.831	0.804	0.814
	(1.36)	(1.43)	(1.38)	(1.40)
R^2	0.9309	0.9309	0.9311	0.9310
Observations	676	676	676	676

Notes: The table presents estimates of different measures of innovation on the top 1% income share of country income. I consider different measures of innovation which are all lagged by 1 year and standardized by country population: column (1) uses the number of citations received within a three-year window, column (2) uses the time elapsed between the filing date of the application and the date of the grant, column (3) uses the number of patents weighted by their generality index and column (4) uses the number of claims. All these measures as well as the dependent variable are taken in log. Number of countries: 31 for all columns. Time span: 1978-2013 for all columns.

Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***,** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance

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Table 9: TOP 1% INCOME SHARE AND INNOVATION

Dependent variable	Top 1% Income Share			
	(1)	**(2)**	**(3)**	**(4)**
Measure of innovation	Cit3	Grant lag	Generality	Claims
Innovation	0.0307**	0.0310**	0.0359*	0.0337**
	(2.21)	(2.05)	(1.80)	(2.14)
Sharefinance	-0.0277	-0.0270	-0.0328	-0.0307
	(-0.56)	(-0.54)	(-0.66)	(-0.62)
Popgrowth	0.0244	0.0242	0.0247	0.0259
	(1.08)	(1.13)	(1.09)	(1.21)
Gvtsize	-2.431**	-2.478**	-2.448**	-2.453**
	(-2.11)	(-2.17)	(-2.13)	(-2.16)
Unemployment	1.013**	1.034**	1.015**	1.025**
	(2.27)	(2.26)	(2.27)	(2.27)
Gdppcgr	0.895**	0.866**	0.851**	0.886**
	(2.36)	(2.26)	(2.19)	(2.41)
R^2	0.9305	0.9301	0.9303	0.9306
Observations	676	676	676	676

Notes: The table presents estimates of different measures of innovation on the top 1% income share of country income. I consider different measures of innovation which are all lagged by 1 year and standardized by country population: column (1) uses the number of citations received within a three-year window, column (2) uses the time elapsed between the filing date of the application and the date of the grant, column (3) uses the number of patents weighted by their generality index and column (4) uses the number of claims. All these measures as well as the dependent variable are taken in log.Number of countries: 31 for all columns. Time span: 1978-2013 for all columns.

Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***,** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 10: TOP 1% INCOME SHARE AND INNOVATION

Dependent variable	Top 1% Income Share			
	(1)	**(2)**	**(3)**	**(4)**
Measure of innovation	Cit5	Grant lag	Generality	Claims
Innovation	0.0292**	0.0383**	0.0420**	0.0387**
	(2.12)	(2.38)	(2.04)	(2.33)
Sharefinance	-0.0604	-0.0602	-0.0655	-0.0641
	(-1.02)	(-1.04)	(-1.14)	(-1.10)
Popgrowth	-0.00290	-0.00389	-0.00250	-0.00201
	(-0.14)	(-0.20)	(-0.12)	(-0.10)
Gvtsize	-2.779**	-2.805**	-2.768**	-2.802**
	(-2.40)	(-2.49)	(-2.40)	(-2.48)
Unemployment	1.309**	1.313**	1.281**	1.293**
	(2.51)	(2.54)	(2.55)	(2.52)
Gdppc	0.825	0.889	0.859	0.869
	(1.40)	(1.54)	(1.48)	(1.50)
R^2	0.928	0.928	0.928	0.928
Observations	649	649	649	649

Notes: The table presents estimates of different measures of innovation on the top 1% income share of country income. I consider different measures of innovation which are all lagged by 1 year and standardized by country population: column (1) uses the number of citations received within a five-year window, column (2) uses the time elapsed between the filing date of the application and the date of the grant, column (3) uses the number of patents weighted by their generality index and column (4) uses the number of claims. All these measures as well as the dependent variable are taken in log. Number of countries: 31 for all columns. Time span: 1978-2011 for all columns.

Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***,** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 11: TOP 1% INCOME SHARE AND INNOVATION

Dependent variable	Top 1% Income Share			
	(1)	**(2)**	**(3)**	**(4)**
Measure of innovation	Cit5	Grant lag	Generality	Claims
Innovation	0.0260**	0.0307**	0.0349*	0.0331**
	(1.99)	(2.04)	(1.75)	(2.12)
Sharefinance	-0.0234	-0.0224	-0.0279	-0.0261
	(-0.45)	(-0.44)	(-0.55)	(-0.52)
Popgrowth	0.0243	0.0238	0.0243	0.0254
	(1.03)	(1.05)	(1.02)	(1.12)
Gvtsize	-2.381**	-2.453**	-2.422**	-2.427**
	(-2.00)	(-2.08)	(-2.04)	(-2.07)
Unemployment	1.109**	1.093**	1.073**	1.082**
	(2.39)	(2.33)	(2.32)	(2.33)
Gdppcgr	0.911**	0.867**	0.854**	0.888**
	(2.29)	(2.16)	(2.10)	(2.30)
R^2	0.927	0.927	0.927	0.927
Observations	649	649	649	649

Notes: The table presents estimates of different measures of innovation on the top 1% income share of country income. I consider different measures of innovation which are all lagged by 1 year and standardized by country population: column (1) uses the number of citations received within a five-year window, column (2) uses the time elapsed between the filing date of the application and the date of the grant, column (3) uses the number of patents weighted by their generality index and column (4) uses the number of claims. All these measures as well as the dependent variable are taken in log. Number of countries: 31 for all columns. Time span: 1978-2011 for all columns.

Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***,** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 12: TOP 1% INCOME SHARE AND INNOVATION

Dependent variable	Top 1% Income Share			
	(1)	**(2)**	**(3)**	**(4)**
Measure of innovation	Cit7	Grant lag	Generality	Claims
Innovation	0.0270**	0.0393**	0.0415**	0.0388**
	(2.00)	(2.40)	(1.99)	(2.29)
Sharefinance	-0.0585	-0.0623	-0.0657	-0.0665
	(-0.88)	(-0.96)	(-1.02)	(-1.03)
Popgrowth	-0.00295	-0.00529	-0.00353	-0.00330
	(-0.12)	(-0.25)	(-0.15)	(-0.15)
Gvtsize	-2.717**	-2.750**	-2.711**	-2.753**
	(-2.28)	(-2.37)	(-2.28)	(-2.37)
Unemployment	1.379**	1.364**	1.338**	1.342**
	(2.51)	(2.53)	(2.54)	(2.50)
Gdppc	0.878	0.958	0.924	0.936
	(1.42)	(1.60)	(1.53)	(1.55)
R^2	0.924	0.925	0.925	0.925
Observations	609	609	609	609

Notes: The table presents estimates of different measures of innovation on the top 1% income share of country income. I consider different measures of innovation which are all lagged by 1 year and standardized by country population: column (1) uses the number of citations received within a seven-year window, column (2) uses the time elapsed between the filing date of the application and the date of the grant, column (3) uses the number of patents weighted by their generality index and column (4) uses the number of claims. All these measures as well as the dependent variable are taken in log. Number of countries: 31 for all columns. Time span: 1978-2009 for all columns.

Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***,** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 13: TOP 1% INCOME SHARE AND INNOVATION

Dependent variable	Top 1% Income Share			
	(1)	(2)	(3)	(4)
Measure of innovation	Cit7	Grant lag	Generality	Claims
Innovation	0.0237*	0.0307**	0.0335*	0.0323**
	(1.86)	(1.99)	(1.65)	(2.00)
Sharefinance	-0.0167	-0.0183	-0.0222	-0.0224
	(-0.28)	(-0.32)	(-0.40)	(-0.40)
Popgrowth	0.0257	0.0245	0.0253	0.0260
	(0.97)	(0.96)	(0.95)	(1.03)
Gvtsize	-2.231*	-2.305*	-2.273*	-2.287*
	(-1.82)	(-1.90)	(-1.85)	(-1.89)
Unemployment	1.161**	1.128**	1.115**	1.115**
	(2.33)	(2.26)	(2.26)	(2.25)
Gdppcgr	0.961**	0.916**	0.908**	0.939**
	(2.32)	(2.19)	(2.13)	(2.34)
R^2	0.923	0.923	0.923	0.923
Observations	609	609	609	609

Notes: The table presents estimates of different measures of innovation on the top 1% income share of country income. I consider different measures of innovation which are all lagged by 1 year and standardized by country population: column (1) uses the number of citations received within a seven-year window, column (2) uses the time elapsed between the filing date of the application and the date of the grant, column (3) uses the number of patents weighted by their generality index and column (4) uses the number of claims. All these measures as well as the dependent variable are taken in log. Number of countries: 31 for all columns. Time span: 1978-2009 for all columns.

Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***,** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 14: INNOVATION AND VARIOUS MEASURES OF INEQUALITY

Dependent variable	Top 1% (1)	Avgtop (2)	Top 10% (3)	Overall Gini (S) (4)	Overall Gini (L) (5)	G99 (S) (6)	G99 (L) (7)
Innovation	0.0265*	0.00686	0.0120	0.0102	0.0145	0.00797	0.0128
	(1.77)	(0.85)	(1.41)	(1.07)	(1.45)	(0.72)	(1.07)
Sharefinance	-0.0479	0.0130	-0.0111	0.0227	0.0437*	0.0441**	0.0708**
	(-0.78)	(0.49)	(-0.43)	(1.19)	(1.87)	(2.02)	(2.57)
Popgrowth	-0.000523	-0.0185**	-0.0168*	-0.00824	-0.0133	-0.00403	-0.00983
	(-0.02)	(-2.22)	(-1.82)	(-0.92)	(-0.93)	(-0.37)	(-0.55)
Gvtsize	-2.988**	0.166	-0.857	-0.573*	-0.773*	-0.147	-0.266
	(-2.44)	(0.25)	(-1.49)	(-1.80)	(-1.67)	(-0.39)	(-0.39)
Unemployment	1.154*	0.737***	0.797***	0.603***	0.725***	0.647***	0.810***
	(1.91)	(4.20)	(3.76)	(2.84)	(3.65)	(2.70)	(3.59)
Gdppc	0.757	0.0249	0.136	-0.0895	-0.0728	-0.146	-0.110
	(1.10)	(0.15)	(0.63)	(-0.32)	(-0.29)	(-0.56)	(-0.45)
R^2	0.923	0.896	0.935	0.894	0.880	0.866	0.851
Observations	612	612	612	612	612	612	612

Notes: The table presents estimates of one measure of innovation (citations received within a five-year window per inhabitants) on various measures of inequality: column (1) uses the top 1% income share, column (2) uses the average size of percentiles 2 to 10 in the income distribution, column (3) uses the 10% income share, column (4) uses the Gini coefficient with small standard deviation, column (5) uses the Gini coefficient with big standard deviation, column (6) uses the Gini coefficient with small standard deviation excluding the first percentile of the income distribution and column (7) uses the Gini coefficient with big standard deviation excluding the first percentile of the income distribution. Innovation measures have been lagged by 1 year and are taken in log. The dependent variable is also in log in all columns. Number of countries: 28 for all columns. Time span: 1978-2011 for all columns.

Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 15: INNOVATION AND VARIOUS MEASURES OF INEQUALITY

Dependent variable	Top 1%	Avgtop	Top 10%	Overall Gini (S)	Overall Gini (L)	G99 (S)	G99 (L)
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Innovation	0.0368**	0.0120	0.0187*	0.0138	0.0175	0.0103	0.0143
	(1.99)	(1.30)	(1.92)	(1.36)	(1.58)	(0.83)	(1.04)
Sharefinance	-0.0518	0.0108	-0.0139	0.0213	0.0428*	0.0432**	0.0705**
	(-0.86)	(0.41)	(-0.55)	(1.12)	(1.83)	(1.98)	(2.56)
Popgrowth	-0.0000466	-0.0184**	-0.0166*	-0.00805	-0.0130	-0.00388	-0.00959
	(-0.00)	(-2.25)	(-1.90)	(-0.88)	(-0.89)	(-0.35)	(-0.53)
Gvtsize	-3.046**	0.156	-0.879	-0.596*	-0.810*	-0.166	-0.300
	(-2.55)	(0.24)	(-1.59)	(-1.88)	(-1.72)	(-0.43)	(-0.43)
Unemployment	1.136*	0.734***	0.790***	0.596***	0.714***	0.641***	0.800***
	(1.92)	(4.36)	(3.91)	(2.81)	(3.68)	(2.68)	(3.63)
Gdppc	0.789	0.0381	0.155	-0.0775	-0.0599	-0.138	-0.100
	(1.16)	(0.23)	(0.73)	(-0.28)	(-0.25)	(-0.55)	(-0.43)
R^2	0.924	0.898	0.936	0.896	0.881	0.866	0.851
Observations	612	612	612	612	612	612	612

Notes: The table presents estimates of one measure of innovation (the number of claims) on various measures of inequality: column (1) uses the top 1% income share, column (2) uses the average size of percentiles 2 to 10 in the income distribution, column (3) uses the 10% income share, column (4) uses the Gini coefficient with small standard deviation, column (5) uses the Gini coefficient with big standard deviation, column (6) uses the Gini coefficient with small standard deviation excluding the first percentile of the income distribution and column (7) uses the Gini coefficient with big standard deviation excluding the first percentile of the income distribution. Innovation measures have been lagged by 1 year and are taken in log. The dependent variable is also in log in all columns. Number of countries: 28 for all columns. Time span: 1978-2011 for all columns.

Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 16: INNOVATION AND VARIOUS MEASURES OF INEQUALITY

Dependent variable	Top 1%	Avgtop	Top 10%	Overall Gini (S)	Overall Gini (L)	G99 (S)	G99 (L)
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Innovation	0.0375*	0.0107	0.0179	0.0148	0.0218**	0.0114	0.0191
	(1.65)	(1.07)	(1.56)	(1.51)	(2.16)	(0.95)	(1.48)
Sharefinance	-0.0524	0.0113	-0.0136	0.0208	0.0406*	0.0426*	0.0681**
	(-0.88)	(0.43)	(-0.54)	(1.08)	(1.73)	(1.93)	(2.45)
Popgrowth	-0.000207	-0.0184**	-0.0166*	-0.00812	-0.0131	-0.00394	-0.00969
	(-0.01)	(-2.23)	(-1.84)	(-0.92)	(-0.93)	(-0.37)	(-0.55)
Gvtsize	-2.988**	0.170	-0.854	-0.572*	-0.769*	-0.147	-0.262
	(-2.46)	(0.25)	(-1.51)	(-1.81)	(-1.72)	(-0.39)	(-0.39)
Unemployment	1.125*	0.730***	0.784***	0.592***	0.710***	0.638***	0.796***
	(1.92)	(4.33)	(3.90)	(2.84)	(3.62)	(2.70)	(3.57)
Gdppc	0.781	0.0329	0.149	-0.0794	-0.0574	-0.138	-0.0961
	(1.15)	(0.20)	(0.70)	(-0.29)	(-0.23)	(-0.54)	(-0.41)
R^2	0.923	0.897	0.935	0.895	0.883	0.866	0.852
Observations	612	612	612	612	612	612	612

Notes: The table presents estimates of one measure of innovation (the number of patents weighted by their generality index) on various measures of inequality: column (1) uses the top 1% income share, column (2) uses the average size of percentiles 2 to 10 in the income distribution, column (3) uses the 10% income share, column (4) uses the Gini coefficient with small standard deviation, column (5) uses the Gini coefficient with big standard deviation, column (6) uses the Gini coefficient with small standard deviation excluding the first percentile of the income distribution and column (7) uses the Gini coefficient with big standard deviation excluding the first percentile of the income distribution. Innovation measures have been lagged by 1 year and are taken in log. The dependent variable is also in log in all columns. Number of countries: 28 for all columns. Time span: 1978-2011 for all columns.

Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 17: INNOVATION AND VARIOUS MEASURES OF INEQUALITY

Dependent variable	Top 1% (1)	Avgtop (2)	Top 10% (3)	Overall Gini (S) (4)	Overall Gini (L) (5)	G99 (S) (6)	G99 (L) (7)
Innovation	0.0364**	0.0111	0.0177*	0.0143	0.0175	0.0115	0.0148
	(2.11)	(1.20)	(1.89)	(1.41)	(1.55)	(0.94)	(1.07)
Sharefinance	-0.0481	0.0123	-0.0117	0.0225	0.0444*	0.0438**	0.0717***
	(-0.80)	(0.46)	(-0.47)	(1.20)	(1.91)	(2.02)	(2.60)
Popgrowth	-0.00127	-0.0187**	-0.0172*	-0.00854	-0.0136	-0.00427	-0.0101
	(-0.06)	(-2.26)	(-1.93)	(-0.90)	(-0.90)	(-0.38)	(-0.54)
Gvtsize	-3.027**	0.161	-0.872	-0.587*	-0.800*	-0.158	-0.291
	(-2.53)	(0.24)	(-1.54)	(-1.89)	(-1.70)	(-0.41)	(-0.42)
Unemployment	1.156*	0.739***	0.799***	0.604***	0.724***	0.648***	0.808***
	(1.94)	(4.33)	(3.92)	(2.89)	(3.77)	(2.72)	(3.67)
Gdppc	0.806	0.0418	0.162	-0.0696	-0.0513	-0.130	-0.0922
	(1.18)	(0.25)	(0.77)	(-0.26)	(-0.21)	(-0.52)	(-0.40)
R^2	0.924	0.897	0.936	0.896	0.881	0.867	0.851
Observations	612	612	612	612	612	612	612

Notes: The table presents estimates of one measure of innovation (the time elapsed between the filing date of the application and the date of the grant) on various measures of inequality: column (1) uses the top 1% income share, column (2) uses the average size of percentiles 2 to 10 in the income distribution, column (3) uses the 10% income share, column (4) uses the Gini coefficient with small standard deviation, column (5) uses the Gini coefficient with big standard deviation, column (6) uses the Gini coefficient with small standard deviation excluding the first percentile of the income distribution and column (7) uses the Gini coefficient with big standard deviation excluding the first percentile of the income distribution. Innovation measures have been lagged by 1 year and are taken in log. The dependent variable is also in log in all columns. Number of countries: 28 for all columns. Time span: 1978-2011 for all columns.
Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 18: TOP 1% INCOME SHARE AND INNOVATION AT DIFFERENT LAGS

Dependent variable	Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Lag of innovation	1 year	2 years	3 years	4 years	5 years	6 years
Innovation	0.0560***	0.0497***	0.0431**	0.0319**	0.0268*	0.0131
	(2.90)	(2.81)	(2.56)	(2.10)	(1.83)	(0.89)
Gdppc	1.010	1.001	0.931	0.849	0.850	0.791
	(1.33)	(1.29)	(1.17)	(1.03)	(1.04)	(0.94)
Popgrowth	-0.0141	-0.0156	-0.0152	-0.0153	-0.0158	-0.0130
	(-0.70)	(-0.77)	(-0.76)	(-0.73)	(-0.71)	(-0.58)
Gvtsize	-2.508**	-2.472**	-2.465**	-2.451*	-2.461*	-2.517*
	(-2.05)	(-2.01)	(-2.00)	(-1.93)	(-1.93)	(-1.93)
Unemployment	0.671	0.753	0.830	0.837	0.845	0.854
	(1.37)	(1.49)	(1.59)	(1.53)	(1.49)	(1.45)
Sharefinance	-0.0577	-0.0522	-0.0533	-0.0566	-0.0588	-0.0558
	(-1.11)	(-0.98)	(-0.99)	(-1.03)	(-1.05)	(-0.96)
R^2	0.936	0.936	0.935	0.934	0.933	0.932
Observations	555	555	555	555	555	555

Notes: The table presents estimates of one measure of innovation (citations received within a three-year window per inhabitants) on the top 1% income share at different lags column (1) uses a one-year lag between the measure of innovation and the dependent variable, column (2) uses two-year lags etc. Both our measure of innovation and the dependent variable are taken in log in all columns. Number of countries: 28 for all columns. Time span: 1983-2013 for all columns.

Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***,** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 19: TOP 1% INCOME SHARE AND INNOVATION AT DIFFERENT LAGS

Dependent variable	Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Lag of innovation	1 year	2 years	3 years	4 years	5 years	6 years
Innovation	0.0617***	0.0466**	0.0403**	0.0317*	0.0275	0.0141
	(2.76)	(2.31)	(2.04)	(1.80)	(1.64)	(0.89)
Gdppc	1.125	1.057	0.971	0.911	0.914	0.872
	(1.47)	(1.34)	(1.19)	(1.08)	(1.09)	(1.02)
Popgrowth	-0.0187	-0.0177	-0.0159	-0.0157	-0.0166	-0.0148
	(-0.92)	(-0.86)	(-0.81)	(-0.76)	(-0.76)	(-0.67)
Gvtsize	-2.549**	-2.465*	-2.452*	-2.398*	-2.426*	-2.470*
	(-2.04)	(-1.93)	(-1.90)	(-1.84)	(-1.86)	(-1.86)
Unemployment	0.708	0.838	0.913	0.901	0.903	0.906
	(1.33)	(1.52)	(1.63)	(1.56)	(1.52)	(1.47)
Sharefinance	-0.0575	-0.0522	-0.0524	-0.0555	-0.0563	-0.0513
	(-1.07)	(-0.93)	(-0.94)	(-0.99)	(-0.99)	(-0.87)
R^2	0.934	0.932	0.931	0.930	0.930	0.929
Observations	528	528	528	528	528	528

Notes: The table presents estimates of one measure of innovation (citations received within a five-year window per inhabitants) on the top 1% income share at different lags column (1) uses a one-year lag between the measure of innovation and the dependent variable, column (2) uses two-year lags etc. Both our measure of innovation and the dependent variable are taken in log in all columns. Number of countries: 28 for all columns. Time span: 1983-2011 for all columns.
Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***,** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 20: TOP 1% INCOME SHARE AND INNOVATION AT DIFFERENT LAGS

Dependent variable	Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Lag of innovation	1 year	2 years	3 years	4 years	5 years	6 years
Innovation	0.0629***	0.0445**	0.0404*	0.0309*	0.0242	0.0104
	(2.68)	(2.14)	(1.92)	(1.70)	(1.46)	(0.67)
Gdppc	1.246	1.164	1.085	1.022	1.020	0.984
	(1.58)	(1.42)	(1.28)	(1.16)	(1.16)	(1.11)
Popgrowth	-0.0209	-0.0193	-0.0174	-0.0178	-0.0184	-0.0160
	(-0.95)	(-0.85)	(-0.82)	(-0.80)	(-0.78)	(-0.67)
Gvtsize	-2.563**	-2.437*	-2.439*	-2.366*	-2.377*	-2.388*
	(-1.99)	(-1.85)	(-1.83)	(-1.75)	(-1.75)	(-1.74)
Unemployment	0.726	0.863	0.925	0.918	0.920	0.919
	(1.22)	(1.40)	(1.50)	(1.46)	(1.42)	(1.38)
Sharefinance	-0.0602	-0.0536	-0.0527	-0.0550	-0.0551	-0.0491
	(-0.97)	(-0.83)	(-0.83)	(-0.87)	(-0.85)	(-0.74)
R^2	0.931	0.929	0.928	0.927	0.926	0.925
Observations	490	490	490	490	490	490

Notes: The table presents estimates of one measure of innovation (citations received within a seven-year window per inhabitants) on the top 1% income share at different lags column (1) uses a one-year lag between the measure of innovation and the dependent variable, column (2) uses two-year lags etc. Both our measure of innovation and the dependent variable are taken in log in all columns. Number of countries: 27 for all columns. Time span: 1983-2009 for all columns.

Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***,** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 21: TOP 1% INCOME SHARE AND INNOVATION AT DIFFERENT LAGS

Dependent variable	Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Lag of innovation	1 year	2 years	3 years	4 years	5 years	6 years
Innovation	0.0700***	0.0632***	0.0604***	0.0443**	0.0284	0.0168
	(2.75)	(2.93)	(2.86)	(2.29)	(1.51)	(0.94)
Gdppc	1.179	1.135	1.078	0.980	0.941	0.893
	(1.57)	(1.48)	(1.36)	(1.19)	(1.14)	(1.06)
Popgrowth	-0.0181	-0.0201	-0.0219	-0.0183	-0.0176	-0.0164
	(-1.00)	(-1.03)	(-1.18)	(-0.92)	(-0.79)	(-0.73)
Gvtsize	-2.492**	-2.514**	-2.541**	-2.481*	-2.479*	-2.487*
	(-2.06)	(-2.06)	(-2.08)	(-1.96)	(-1.90)	(-1.86)
Unemployment	0.720	0.790	0.871	0.886	0.890	0.903
	(1.38)	(1.47)	(1.59)	(1.56)	(1.49)	(1.47)
Sharefinance	-0.0653	-0.0622	-0.0604	-0.0594	-0.0557	-0.0515
	(-1.25)	(-1.15)	(-1.11)	(-1.07)	(-0.97)	(-0.87)
R^2	0.934	0.934	0.934	0.932	0.930	0.929
Observations	528	528	528	528	528	528

Notes: The table presents estimates of one measure of innovation (Total number of claims associated with patents per inhabitants) on the top 1% income share at different lags column (1) uses a one-year lag between the measure of innovation and the dependent variable, column (2) uses two-year lags etc. Both our measure of innovation and the dependent variable are taken in log in all columns. Number of countries: 28 for all columns. Time span: 1983-2011 for all columns.

Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***,** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 22: TOP 1% INCOME SHARE AND INNOVATION AT DIFFERENT LAGS

Dependent variable	Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Lag of innovation	1 year	2 years	3 years	4 years	5 years	6 years
Innovation	0.0690***	0.0598***	0.0550**	0.0417**	0.0250	0.0106
	(2.67)	(2.60)	(2.53)	(2.17)	(1.28)	(0.61)
Gdppc	1.163	1.125	1.048	0.961	0.913	0.877
	(1.56)	(1.46)	(1.31)	(1.16)	(1.10)	(1.04)
Popgrowth	-0.0149	-0.0175	-0.0174	-0.0164	-0.0157	-0.0151
	(-0.77)	(-0.90)	(-0.90)	(-0.80)	(-0.70)	(-0.65)
Gvtsize	-2.414*	-2.384*	-2.402*	-2.424*	-2.471*	-2.502*
	(-1.95)	(-1.91)	(-1.91)	(-1.88)	(-1.88)	(-1.85)
Unemployment	0.732	0.790	0.865	0.900	0.907	0.901
	(1.40)	(1.48)	(1.59)	(1.58)	(1.51)	(1.45)
Sharefinance	-0.0638	-0.0590	-0.0583	-0.0561	-0.0525	-0.0487
	(-1.20)	(-1.08)	(-1.07)	(-1.00)	(-0.90)	(-0.82)
R^2	0.934	0.933	0.933	0.931	0.929	0.928
Observations	528	528	528	528	528	528

Notes: The table presents estimates of one measure of innovation (Total number of patents weighted by the generality index per inhabitants) on the top 1% income share at different lags column (1) uses a one-year lag between the measure of innovation and the dependent variable, column (2) uses two-year lags etc. Both our measure of innovation and the dependent variable are taken in log in all columns. Number of countries: 28 for all columns. Time span: 1983-2011 for all columns.

Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***,** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 23: TOP 1% INCOME SHARE AND INNOVATION AT DIFFERENT LAGS

Dependent variable	Top 1% Income Share					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Lag of innovation	1 year	2 years	3 years	4 years	5 years	6 years
Innovation	0.0728***	0.0585***	0.0530***	0.0386**	0.0211	0.0108
	(3.27)	(2.82)	(2.80)	(2.16)	(1.13)	(0.59)
Gdppc	1.298*	1.209	1.105	0.992	0.927	0.887
	(1.78)	(1.60)	(1.41)	(1.21)	(1.12)	(1.06)
Popgrowth	-0.0204	-0.0201	-0.0198	-0.0183	-0.0168	-0.0162
	(-1.12)	(-1.02)	(-1.01)	(-0.88)	(-0.73)	(-0.67)
Gvtsize	-2.443**	-2.430**	-2.443**	-2.442*	-2.456*	-2.501*
	(-2.06)	(-1.99)	(-2.01)	(-1.92)	(-1.87)	(-1.86)
Unemployment	0.758	0.848	0.909	0.919	0.909	0.906
	(1.43)	(1.54)	(1.61)	(1.57)	(1.48)	(1.45)
Sharefinance	-0.0635	-0.0567	-0.0551	-0.0534	-0.0498	-0.0476
	(-1.23)	(-1.05)	(-1.01)	(-0.94)	(-0.83)	(-0.78)
R^2	0.935	0.933	0.932	0.931	0.929	0.928
Observations	528	528	528	528	528	528

Notes: The table presents estimates of one measure of innovation (Time elapsed between the filing date of the application and the date of the grant) on the top 1% income share at different lags column (1) uses a one-year lag between the measure of innovation and the dependent variable, column (2) uses two-year lags etc. Both our measure of innovation and the dependent variable are taken in log in all columns. Number of countries: 28 for all columns. Time span: 1983-2011 for all columns.
Panel data OLS regressions with country and year fixed effects. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***,** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

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Table 24: REGRESSION OF INNOVATION ON TOP 1% INCOME SHARE USING LAGS AS INSTRUMENTS

Dependent Variable	Top 1% Income Share				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
Measure of Innovation	Cit5	Claims	Generality	Grant lag	Patent (W)
Innovation	0.0199**	0.0223**	0.0221*	0.0180*	0.0291
	(2.35)	(2.07)	(1.94)	(1.67)	(1.27)
L.Top1	0.706***	0.706***	0.752***	0.710***	0.424
	(5.87)	(5.58)	(7.60)	(6.67)	(1.42)
Gvtsize	-5.738***	-6.318***	-5.902***	-6.278***	-3.562*
	(-4.43)	(-4.32)	(-3.95)	(-3.63)	(-1.68)
Gdppc	-0.350	-0.188	0.00801	-0.131	0.134
	(-0.63)	(-0.35)	(0.02)	(-0.17)	(0.18)
Unemployment	2.233**	2.236**	2.521***	2.381***	-0.236
	(2.55)	(2.41)	(2.88)	(2.64)	(-0.14)
Sharefinance	0.239***	0.258***	0.204**	0.258*	0.128
	(2.97)	(2.72)	(2.46)	(1.84)	(0.56)
Popgrowth	0.00721	0.00647	0.0107	0.0130	-0.0296
	(0.34)	(0.27)	(0.55)	(0.53)	(-0.61)
Hansen (p-value)	0.774	0.788	0.771	0.571	0.235
AR(2) (p-value)	0.524	0.648	0.469	0.566	0.394
Observations	562	562	562	562	616

Notes: The table presents estimates of different measures of innovation lagged by one year on the top 1% income share of country income: column (1) uses the number of citations received within a five-year window, column (2) uses the number of claims, column (3) uses the number of patents weighted by their generality index, column (4) uses the time elapsed between the filing date of the application and the date of the grant (5) uses the number of patents weighted by their inventors. All these measures as well as the dependent variable are taken in log. Number of countries: 30 for columns (1) to (4) and 31 for column (5). Time span: 1980-2011 for columns (1) to (4) and 1974-2011 for column (5).

Dynamic panel-data estimation, nolevel two-step difference GMM. Innovation is instrumented by the first five lags, lag of dependent variable is instrumented by the second to fifth lag and the rest of the control variables are instrumented by the first three lags. Total number of instruments: 24. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 25: REGRESSION OF INNOVATION ON TOP 10% INCOME SHARE USING LAGS AS INSTRUMENTS

Dependent Variable	Top 10% Income Share			
	(1)	**(2)**	**(3)**	**(4)**
Measure of Innovation	Cit5	Claims	Generality	Grant lag
Innovation	0.00667*	0.00256	0.00647	0.00700
	(1.71)	(0.22)	(0.55)	(1.29)
L.Top10	0.769***	0.835***	0.813***	0.798***
	(6.75)	(4.39)	(4.85)	(4.83)
Gvtsize	-0.570	-0.398	-0.865	-0.869
	(-1.29)	(-0.46)	(-0.80)	(-1.15)
Gdppc	0.402**	0.503	0.319	0.433*
	(2.14)	(1.04)	(0.65)	(1.81)
Unemployment	0.874***	0.797**	0.863**	0.982***
	(3.03)	(1.97)	(2.15)	(3.41)
Sharefinance	-0.0209	-0.0503	-0.00563	-0.00913
	(-0.85)	(-0.57)	(-0.06)	(-0.16)
Popgrowth	0.00233	0.00328	0.00338	0.00841
	(0.25)	(0.23)	(0.25)	(0.70)
Hansen (p-value)	0.727	0.596	0.729	0.874
AR(2) (p-value)	0.335	0.303	0.342	0.304
Observations	540	540	540	540

Notes: The table presents estimates of different measures of innovation lagged by one year on the top 10% income share of country income: column (1) uses the number of citations received within a five-year window, column (2) uses the number of claims, column (3) uses the number of patents weighted by their generality index and column (4) uses the time elapsed between the filing date of the application and the date of the grant. All these measures as well as the dependent variable are taken in log. Number of countries: 27 for columns (1) to (4). Time span: 1979-2011 for columns (1) to (4).

Dynamic panel-data estimation, nolevel two-step difference GMM. Innovation is instrumented by the first five lags, lag of dependent variable is instrumented by the second to fifth lag and the rest of the control variables are instrumented by the first three lags. Total number of instruments: 24. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 26: REGRESSION OF INNOVATION ON G99 (S) USING LAGS AS INSTRUMENTS

Dependent Variable	G99 (Small Standard Deviation)			
	(1)	**(2)**	**(3)**	**(4)**
Measure of Innovation	Cit5	Claims	Generality	Grant lag
Innovation	-0.00189	-0.00421	-0.00435	-0.0101
	(-0.26)	(-0.67)	(-0.36)	(-0.92)
L. G99(S)	-0.112	-0.0939	-0.133	-0.0901
	(-0.44)	(-0.40)	(-0.47)	(-0.36)
Gvtsize	-1.583	-1.736	-1.723	-1.201
	(-1.45)	(-1.41)	(-1.46)	(-0.79)
Gdppc	-0.199	-0.253	-0.204	-0.220
	(-0.44)	(-0.55)	(-0.42)	(-0.30)
Unemployment	1.032*	0.876	0.939*	0.781
	(1.83)	(1.62)	(1.68)	(1.49)
Sharefinance	0.136	0.147	0.142	0.115
	(1.48)	(1.48)	(1.35)	(0.78)
Popgrowth	-0.00548	-0.00876	-0.00797	-0.00399
	(-0.41)	(-0.74)	(-0.72)	(-0.21)
Hansen (p-value)	0.277	0.289	0.254	0.322
AR(2) (p-value)	0.438	0.429	0.347	0.475
Observations	560	560	560	560

Notes: The table presents estimates of different measures of innovation lagged by one year on the overall Gini index with small standard deviation minus top 1% of income share: column (1) uses the number of citations received within a five-year window, column (2) uses the number of claims, column (3) uses the number of patents weighted by their generality index and column (4) uses the time elapsed between the filing date of the application and the date of the grant Number of countries: 30 for columns (1) to (4). Time span: 1977-2011 for columns (1) to (4).

Dynamic panel-data estimation, nolevel two-step difference GMM. Innovation is instrumented by the first five lags, lag of dependent variable is instrumented by the second to fifth lag and the rest of the control variables are instrumented by the first three lags. Total number of instruments: 24. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 27: REGRESSION OF INNOVATION ON G99 (L) USING LAGS AS INSTRUMENTS

Dependent Variable	G99 (Big Standard Deviation)			
	(1)	**(2)**	**(3)**	**(4)**
Measures of Innovation	Cit5	Claims	Generality	Grant lag
Innovation	-0.000210	-0.00257	-0.00389	-0.00294
	(-0.03)	(-0.41)	(-0.38)	(-0.46)
L. G99(L)	0.319	0.292	0.219	0.288*
	(1.41)	(1.48)	(0.89)	(1.84)
Gvtsize	-1.311	-1.180	-1.365	-1.442
	(-1.41)	(-1.58)	(-1.51)	(-1.51)
Gdppc	-0.391	-0.460	-0.574**	-0.663
	(-0.98)	(-1.16)	(-2.23)	(-1.18)
Unemployment	0.717	0.589	0.645	0.605
	(1.58)	(1.45)	(1.51)	(1.49)
Sharefinance	0.122	0.130	0.145**	0.165
	(1.56)	(1.52)	(2.38)	(1.51)
Popgrowth	0.0253	0.0232*	0.0271	0.0232
	(1.34)	(1.76)	(1.56)	(1.43)
Hansen (p-value)	0.604	0.746	0.790	0.752
AR(2) (p-value)	0.202	0.160	0.119	0.161
Observations	560	560	560	560

Notes: The table presents estimates of different measures of innovation lagged by one year on the overall Gini index with big standard deviation minus top 1% of income share: column (1) uses the number of citations received within a five-year window, column (2) uses the number of claims, column (3) uses the number of patents weighted by their generality index and column (4) uses the time elapsed between the filing date of the application and the date of the grant Number of countries: 30 for columns (1) to (4). Time span: 1978-2011 for columns (1) to (4).

Dynamic panel-data estimation, nolevel two-step difference GMM. Innovation is instrumented by the first five lags, lag of dependent variable is instrumented by the second to fifth lag and the rest of the control variables are instrumented by the first three lags. Total number of instruments: 24. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 28: REGRESSION OF INNOVATION ON GINI INDEX (S) USING LAGS AS INSTRUMENTS

Dependent Variable	Gini index with small standard deviation			
	(1)	**(2)**	**(3)**	**(4)**
Measure of Innovation	Cit5	Claims	Generality	Grant lag
Innovation	-0.00164	-0.00124	-0.00109	-0.00290
	(-0.52)	(-0.40)	(-0.29)	(-0.94)
L.Gini(S)	0.815***	0.795***	0.811***	0.764***
	(6.03)	(5.55)	(5.22)	(5.63)
Gvtsize	-0.398	-0.425	-0.433	-0.345
	(-1.10)	(-1.28)	(-1.19)	(-1.14)
Gdppc	-0.212	-0.219	-0.233	-0.191
	(-1.16)	(-1.32)	(-1.29)	(-1.19)
Unemployment	0.479**	0.523**	0.523**	0.483**
	(2.02)	(2.26)	(2.14)	(2.20)
Sharefinance	0.0484**	0.0491***	0.0496***	0.0442**
	(2.50)	(2.91)	(2.75)	(2.54)
Popgrowth	0.00938	0.00894	0.00976	0.00825
	(0.92)	(0.93)	(1.09)	(0.87)
Hansen (p-value)	0.267	0.384	0.326	0.428
AR(2) (p-value)	0.917	0.934	0.926	0.945
Observations	697	697	697	697

Notes: The table presents estimates of different measures of innovation lagged by one year on the overall Gini index with small standard deviation: column (1) uses the number of citations received within a five-year window, column (2) uses the number of claims, column (3) uses the number of patents weighted by their generality index and column (4) uses the time elapsed between the filing date of the application and the date of the grant Number of countries: 31 for columns (1) to (4). Time span: 1977-2011 for columns (1) to (4).

Dynamic panel-data estimation, nolevel two-step difference GMM. Innovation is instrumented by the first five lags, lag of dependent variable is instrumented by the second to fifth lag and the rest of the control variables are instrumented by the first three lags. Total number of instruments: 24. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 29: REGRESSION OF INNOVATION ON GINI INDEX (L) USING LAGS AS INSTRUMENTS

Dependent Variable	Gini index with big standard deviation			
	(1)	**(2)**	**(3)**	**(4)**
Measure of Innovation	Cit5	Claims	Generality	Grant lag
Innovation	0.00217	0.0000405	0.00225	0.000355
	(0.67)	(0.02)	(0.54)	(0.12)
L.Gini(L)	0.834***	0.813***	0.845***	0.834***
	(5.72)	(5.51)	(6.95)	(4.79)
Gvtsize	-0.291	-0.235	-0.352	-0.293
	(-0.92)	(-0.71)	(-1.11)	(-0.83)
Gdppc	-0.0680	-0.0695	-0.0760	-0.109
	(-0.41)	(-0.37)	(-0.40)	(-0.45)
Unemployment	0.403***	0.340**	0.401***	0.336***
	(2.74)	(2.57)	(2.74)	(2.64)
Sharefinance	0.0248	0.0284	0.0284	0.0342
	(0.86)	(0.99)	(0.98)	(1.07)
Popgrowth	0.0154*	0.0156*	0.0148*	0.0161*
	(1.87)	(1.76)	(1.79)	(1.73)
Hansen (p-value)	0.609	0.605	0.694	0.590
AR(2) (p-value)	0.846	0.800	0.853	0.770
Observations	697	697	697	697

Notes: The table presents estimates of different measures of innovation lagged by one year on the overall Gini index with big standard deviation: column (1) uses the number of citations received within a five-year window, column (2) uses the number of claims, column (3) uses the number of patents weighted by their generality index and column (4) uses the time elapsed between the filing date of the application and the date of the grant Number of countries: 31 for columns (1) to (4). Time span: 1978-2011 for columns (1) to (4).

Dynamic panel-data estimation, nolevel two-step difference GMM. Innovation is instrumented by the first five lags, lag of dependent variable is instrumented by the second to fifth lag and the rest of the control variables are instrumented by the first three lags. Total number of instruments: 24. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.

Table 30: REGRESSION OF INNOVATION ON AVERAGE TOP INCOME SHARE USING LAGS AS INSTRUMENTS

Dependent Variable	Average Top Income Share			
	(1)	**(2)**	**(3)**	**(4)**
Measure of Innovation	Cit5	Claims	Generality	Grant lag
Innovation	0.00340	-0.00510	-0.00372	0.000630
	(0.64)	(-0.54)	(-0.28)	(0.08)
L.Avgtop	0.582***	0.748***	0.736***	0.710***
	(4.68)	(4.88)	(4.29)	(5.55)
Gvtsize	0.519	0.793	0.657	0.549
	(0.77)	(1.50)	(0.93)	(0.99)
Gdppc	0.103	0.244	0.201	0.198
	(0.27)	(1.12)	(0.77)	(0.91)
Unemployment	0.390**	0.0608	0.0982	0.204
	(2.37)	(0.17)	(0.21)	(0.68)
Sharefinance	0.00733	-0.0270	-0.0170	-0.00782
	(0.12)	(-0.57)	(-0.30)	(-0.16)
Popgrowth	0.00725	0.00813	0.00677	0.00990
	(1.09)	(0.89)	(0.69)	(1.15)
Observations	537	537	537	537
Hansen (p-value)	0.799	0.651	0.586	0.765
AR(2) (p-value)	0.367	0.371	0.379	0.364

Notes: The table presents estimates of different measures of innovation lagged by one year on the average top income share of country income: column (1) uses the number of citations received within a five-year window, column (2) uses the number of claims, column (3) uses the number of patents weighted by their generality index and column (4) uses the time elapsed between the filing date of the application and the date of the grant. All these measures as well as the dependent variable are taken in log. Number of countries: 27 for columns (1) to (4). Time span: 1979-2011 for columns (1) to (4).

Dynamic panel-data estimation, nolevel two-step difference GMM. Innovation is instrumented by the first five lags, lag of dependent variable is instrumented by the second to fifth lag and the rest of the control variables are instrumented by the first three lags. Total number of instruments: 24. t/z statistics in parentheses, computed with autocorrelation and heteroskedasticity robust standard errors using the Newey-West variance estimator. ***, ** and * respectively indicate 0.01, 0.05 and 0.1 levels of significance.