“The effect of innovation and technological specialization on income inequality”

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THE EFFECT OF INNOVATION AND TECHNOLOGICAL SPECIALIZATION ON INCOME INEQUALITY

Abstract

Using a panel of 28 European Union countries for the period 2003–2014, the authors provide empirical evidence for the relationship between innovation, technological specialization, and income inequality. The results of the fixed effect panel regressions show two important findings. Firstly, the positive link was found between innovation, as measured by patenting activities, and income inequality as measured by Gini index and the top 10% income shares of the richest. Secondly, the authors also found the positive correlation between technological specialization, as measured by the Coefficient of Variances (CV) of Revealed Technological Advantage Index, and income inequality. Overall, the study enriches the previous literature suggesting that innovation may increase the gap of income distribution through the mechanism of Skill-Biased Technical Change (SBTC) and the Schumpeterian view of entrepreneurial rent. More importantly, this study is the first which found that not only the level of innovation does matter to the income distribution, but also how the innovation activities are specialized or diversified. Concentrating the activities into few narrow sectors (i.e., increase technological specialization) may also lead to the increase of income inequality.

Keywords innovation, patenting, technological specialization, income inequality, Gini index

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INTRODUCTION

Income inequality is now regarded as one of the most crucial social problems. Not only because it hampers the economic performance (Stiglitz, 2012), but it also has a direct impact on social instability (Wilkinson & Pickett, 2010). In most of the developed countries, income inequality is considerably higher than three decades ago and even reaches its highest level for the past half of century (Atkinson, 2013). These facts are no longer relevant to the inverted U-curve theory introduced by Kuznets (1955), which stresses that income inequality tends to decline in rich countries along with their economics development. Thus, in recent years, many studies have been conducted to find the explanation: what determines the rise of income inequality.

One should consider the effect of innovation as the determinant of the rising gap between rich and poor. It is inevitable that innovation plays a key role in long-term economic growth (Aghion-Howitt, 1992; Schumpeter, 1942; Solow, 1957). Nevertheless, since the last revolution of digital technology, concern has been raised regarding how the benefits of innovation are distributed: whether they are evenly distributed to the whole of the society or are only concentrated in a small number of individuals. This concern is supported by the fact that the rapid increase of income inequality has been going along with the rapid technological changes started from the 1980s (Atkinson, 2013).

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Moreover, aside from the role of innovation activities in affecting income inequality, the role of diversification and specialization should also be considered. The next question is: which one is worse for the distribution of income, diversifying the innovation activities across wide sectors (i.e., increase technological diversification) or concentrating the innovation activities only into few sectors (i.e., increase technological specialization)? A study from Cantwell and Vertova (2004) found that at the end of 20th century, most of the countries increasingly concentrated their innovation activities on few specific sectors. Therefore, it is also interesting to find out whether technological specialization may also lead to the rise of income inequality.

In this study, we contribute to the discourse by providing empirical evidence from panel regression analysis at the European Union (EU) country level to show that innovation activity and technological specialization could increase income inequality. This study supports the existing empirical research regarding innovation-income inequality relationship, which is still limited. The novelty of the study particularly is on the relationship between technological specialization and income inequality. While Hartmann, Guevara, Jara-Figueroa, Aristarán, and Hidalgo (2017) found the relationship between trade specialization and income inequality, this study is the first which focuses on the technological specialization or innovation activity.

EU countries are considered as the unit of analysis for several reasons. Firstly, it is chosen due to the recent trends of innovativeness and inequality over decades in Europe, which tend to follow parallel growths. On the one hand, most European countries are classified as the most innovative countries in the world. Eight of ten most innovative countries ranked by The Global Innovation Index 2016 originate from the European continent. On the other hand, at the same time, most of them are also challenged by the rise of inequality problems over periods. Secondly, there is less evidence linking innovation and inequality in European case in comparison to those in the U.S. While the recent study from Aghion, Akcigit, Bergeaud, Blundell, and Hémous (2015) found the positive correlation between innovation and top income inequality in the U.S., the curiosity is then being raised whether the identical conclusion is also there in Europe. Thirdly, a practical reason is that the dataset for supporting European study is well provided.

1. HYPOTHESES DEVELOPMENT

In this section, we propose the theoretical framework to support our hypotheses in this study. The first hypothesis is that innovation increases income inequality. We support this statement by proposing the skill biased technical change framework to explain that the benefit of innovation is not fairly distributed among low, middle, and high skilled labor. Additionally, we propose the role of entrepreneurial rent introduced by Joseph Schumpeter (1942) as the determinant of the increasing gap between top income earners and the rest of the population. The second hypothesis in this study is that technological specialization also increases income inequality. The mechanism could be explained through two channels: because innovation increases between sector wage differential and within sector wage differential as well, which will be elaborated in the following section.

H1: Innovation increases income inequality.

We provide two theoretical arguments to support the first tested hypothesis that innovation increases income inequality. Firstly, the relationship is explained by the theory of Skill-Biased Technical Change (SBTC). While traditionally technological change is noticed as a neutral factor, the SBTC theory suggests that instead of affecting all workers evenly, technological change (i.e., innovation) may be skill 'biased': it benefits for high-skilled workers, but harms those with low skills (Acemoglu, 1998; Violante, 2008). The introduction of new technologies increases the demand for skilled labor relative to unskilled labor. In the last three decades, the wage of skilled labor has increased dramatically in relation to unskilled labor. It was shown by the increase in wage differentials by education in the relative earnings of college graduation. On the other hand, workers without college degrees were challenged with the stagnation of wages (Katz & Murphy, 1992).

Aside from the increase in wage differentials, there was a large increase in the supply of educated labor during the period. In the U.S., for instance, the

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number of college enrolment was more than doubled between 1960 and 1980. In the basic economy concept, higher supply leads to lower prices. However, in this case, the abundant amount of high skilled labor supply from college did not push down their relative wages. The combination of higher wage and growing supply means that the relative demand for high skilled labor increased even faster than supply. Here, new technologies are seen as complementary to skills. Hence, an individual whose level of education is higher will be rewarded.

The extended models of SBTC were then introduced by Autor, Levy, and Murnane (2003) and Acemoglu and Autor (2011) to explain the interaction between technological change, skills, and tasks. They found that the demand for workers fell most dramatically for routine tasks, which are characterized by middle-skilled cognitive or manual jobs. Routine tasks such as clerical work, repetitive production, and monitoring jobs are easily codified by machines, and, consequently, the labor input for those tasks declines. On the contrary, the non-routine tasks cannot be replaced by machines. Instead, the non-routine tasks of workers and machines are even complemented by each other. Autor, Levy, and Murnane (2003) divide non-routine tasks into two major categories: (1) abstract tasks that require the high level of education and analytical capability and (2) manual tasks that require more physical activities. The implication is that thus the market labor will be polarized, with the middle-skilled labor, which works for routine jobs, is replaced by machine, while non-routine jobs at the low and high skills distribution have held up relatively well.

Secondly, the rise of income inequality may also be caused by the monopoly rents gained by entrepreneurs due to their innovation activities as suggested by Aghion et al. (2015), Jones and Kim (2014). Both studies emphasize the role of innovation and entrepreneurial efforts, either those who come from incumbents or new entrants. It is not only the skill premium between high-skilled and low skilled-workers, which determines the rise of income inequality, but also the unequal shares of income between entrepreneurs and the whole workers (Aghion et al., 2015). The increase in innovation rate and R&D productivity makes some shares of the aggregate income shift from workers to entrepreneurs. As a result, the income shares of entrepreneurs that are concentrated only in a small number of individuals increase.

Both studies are firstly inspired by Schumpeter's view of growth. According to Schumpeter (1942), the disruptive force of innovation allows the entrepreneurs to enjoy some degree of monopoly rent, which is called by Schumpeter (1942) as "the prizes offered by capitalist society to the successful innovator". The dynamics of market competition occurs, because each firm is motivated by the prospect of monopoly rent. However, this monopoly rent is only temporary, since it then will be destroyed by the next innovation. This role of monopoly rent thus becomes the root of innovation and income inequality discourse, which then was modelled by Aghion et al. (2015), Jones and Kim (2014).

Jones and Kim (2014) define an entrepreneur as a monopolist with the exclusive right to sell a particular product in competition with other varieties. Their basic idea is that innovation determines top income inequality through the interplay between existing entrepreneurs (i.e., incumbents) and the creative destruction of the new entrepreneurs (i.e., new entrants). Based on their Schumpeterian model, the distribution of top income will increase if the entrepreneurial effort of incumbent increases. In other words, temporal monopoly rent will be extended if incumbents expend higher effort or higher productivity to improve their product from their existing ideas. As a result, their income will grow exponentially following the Pareto distribution.

Aghion et al. (2015) highlight the increase of entrepreneurial share as the main factor of the phenomenon. In their model, all of the top income earners are assumed as entrepreneurs who directly benefited from innovation. The basic idea of their model is regarding the important role of innovation-led growth acceleration. According to them, the increase of top income earners is determined by the higher share of entrepreneur due to the increase in innovation rate and R&D productivity. Income inequality increases when some shares of the aggregate income shift from workers to entrepreneurs. As a result, entrepreneur share

of income, which is concentrated only to a small number of people, increases. Reversely, the share of wage income in total income decreases. Those then lead to the increase in total income inequality. Their model also proposes that innovation from both incumbent and new entrant leads to the increase of entrepreneur share, considering that, in both cases, the entrepreneurial share tends to grow larger than wage share.

H2: Technological specialization increases income inequality.

This study considers testing the empirical evidence following the parallel pattern between the growth of specialization and income inequality in recent decades. While the rise of inequality in advanced countries is inevitable, the similar trend is also there for technological specialization. It is, for instance, introduced by the paper of Cantwell and Vertova (2004), which explores the historical evolution of technological diversification in 100-year period from 1890 to 1990. The study found the fact that in the initial condition, more innovative countries tend to be technologically diversified, whereas less innovative countries tend to be more specialized. Interestingly, they found the common tendency that all countries increasingly specialize their innovation activities in the most recent period.

The hypothesis building is also started from the role of 'Skill-Biased Technical Change'. Technological specialization and income inequality may be connected through two channels: (1) through differences in the demand for skilled labor between sectors and (2) through differences in the wage premium across skill levels within the particular sector. Those mechanisms are not mutually exclusive. Instead, they complement each other shaping the worse gap of the income distribution.

First, specialization of innovation activities increases between sector wage differentials, because sectors, which are more innovative, are able to offer higher wages compared to the similar jobs in less innovative sectors. Providing an empirical evidence from occupational employment statistics surveys, Osburn (2000) suggests that inter-industry wage differentials are positively associated with the capital intensity, which represents the high level of technologies and innovation activities. Bartel and Sicherman (1997) stress that firms in sectors, which utilize more sophisticated capital (i.e., more innovative), increase their demands for workers who are adaptive to the new technology (i.e., high-skilled workers). As a consequence, this sector will hire more skilled workers who then shifted from other sectors. Nevertheless, high demands of workers in more innovative sectors do not push wages down as suggested by basic equilibrium theory. In contrast, due to their ability to generate higher productivity, growth, and profit, firms in more innovative sectors are able to pay high-skilled workers much higher than those in less innovative sectors.

This means that Skill-Biased Technical Change is not only about the gap between high- and low-skilled workers, but also refers to the shift of labor from such low-tech to high-tech environment (Bartel & Sicherman, 1997). Consequently, if countries tend to be more specialized in only a few particular sectors, demands for high skilled labor will be asymmetrical and it then leads to the widening gap of inter-industry wages differences. Reversely, if countries diversify their innovation activities into broad sectors, differences of inter-sectoral wages would be suppressed, because the skill premiums are relatively symmetric and more equally distributed across sectors.

Secondly, technological specialization also increases income inequality within sectors. Though sectors with higher innovation activities could generate higher profit, the benefits are biased. Those are only obtained by high-skilled workers as suggested by skill-biased technical change mechanism. Shim and Yang (2017) suggest that the key source of the differences level of job polarization across sectors is inter-sectors wage differentials. Their finding proposes that in the U.S. labor market structure, the progress of job polarization between 1980 and 2009 was more noticeable in sectors that initially paid a high wage premium to workers than in sectors that did not. In other words, high technological sectors suffer higher gap of inequality compared to others.

Firms in a sector with a high wage premium seek alternative ways to minimize production costs

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by substituting middle-skilled workers who perform routine tasks with new technology. This is also supported by the evidence that sector with a high growth rate of ICT capital, as measured of technological changes, exhibits more significant job polarization (Michaels, Natraj, & Van Reenen, 2013), while Levinson (2015) suggests that trade in technology-intensive is only benefited by high-skilled workers by examining trade-inequality relationship in 29 OECD countries through the scope of occupational wages. Beyond its potential growth, high technological sectors leave unintended consequences. Comparing among the rest, this sector generates more obvious job polarization. The growth of the cake is only benefited by high-skilled workers, while those low-skilled workers tend to suffer, as they now face the lower relative demand for their skills (Levinson, 2015).

2. EMPIRICAL METHODS

2.1. Empirical model

To test those hypotheses mentioned above, a series of fixed effect panel regressions are conducted. The empirical study is carried out in 28 countries, which are the members of the European Union in the period 2003–2014 (12 years). The 28 EU countries are Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, and United Kingdom.

We argue that fixed effect test, instead of random effect, is relevant, because it can control all time-invariant differences between countries. In other words, it is assumed that time-invariant characteristic for each country is unique and should not be correlated with others. In the evolutionary perspective, innovation activity, specialization, and income inequality within countries are path dependence. Considering that the trends are determined by historical circumstances, the uniqueness between countries matters to this model. However, to justify the appropriateness of the fixed effect, we also conduct Hausman test.

The model is as follows:

$$\begin{aligned} Y_{it} &= \alpha + \beta_0 innovation_{i(t-h)} + \\ &+ \beta_1 TechSpec_{i(t-h)} + \beta_2 EduHigh_{it} + \\ &+ \beta_3 EduLow_{it} + \beta_4 GovExp_{it} + \\ &+ \beta_5 Openness_{it} + \beta_6 GDPpcap_{it} + \\ &+ \beta_7 Popgrowth_{it} + \beta_8 Unemployment_{it} + \\ &+ v_i + \varepsilon_{it}, \end{aligned} \quad (1)$$

where Y represents the dependent variable which is income inequality in the country i at time t between 2003 and 2014. Innovation stays as the first independent variable, and technological specialization acts as the second independent variable. Subscript h in both independent variables represents time lag effect. Several studies found that the impact of patenting activities on the economic indicators is presented with a time lag of 2 to 3 years after the priority year. Ken et al. (2008) propose that there is a time lag of 4 to 5 years for the patent to give impact to firm profitability in the U.S. pharmaceutical industry. Meanwhile, using panel analysis of German manufacturing industry, Ernst (2001) finds that patent applications affect sales increases with a time-lag of 2 to 3 years after the priority year. To sum up, we assume three years lag of independent variable for the basic model. To check the robustness, we consider the effect of 1 to 5 years of time lag.

Several control variables are included in the model concerning the presence of other potential explanatory variables linked with income inequality. *EduHigh* and *EduLow* represent the percentage of high-educated and low-educated workers, respectively. *GovExp* is government expenditure, as the proportion to *GDP* and *Openness* stands for trade openness index, which represents the level of globalization. α is a constant, while β_n is a coefficient for each variable. Lastly, v and ε are defined as unobserved country-specific characteristics, which are time-invariant effects and idiosyncratic error terms, respectively.

2.2. Variables and data collection

Innovation as the independent variable for testing the first hypothesis is measured by the number of European Patent Office (EPO) patent applications

per inhabitants gathered from Eurostat database. A patent is a document, issued by a government authority, granting an exclusive right for the production or use of a specific new device, apparatus, or process for a stated number of years (Griliches, 1998). Since the patent is regarded as an outcome of the successful innovation process, it is widely accepted that patent statistics can be used as a source of information for measuring innovation and technological change. Previous researchers agree that patents provide a fairly reliable measure of innovation. The strength of patent statistics as compared to alternative measures of innovation activity is due to its "availability in great abundance" (Comanor & Scherer, 1969). Comanor and Scherer (1969), moreover, reject the claim that inability of patent data to reflect inventive quality is fatal for the innovation study. According to them, since creative ability varies across individual, the quality variability problems in patent data are not different from other measures. In other words, other measures of innovation such as trade mark and R&D expenditure are also problematic in the context of representativeness (e.g., not all trademarks reflect innovation and not all R&D expenditure are effectively generating innovation). Furthermore, patent statistics are unique since they provide the long historical time series (Cantwell & Vertova, 2004) and roughly comparable between units of analysis (Lee, 2011).

Meanwhile, technological specialization as the second independent variable is measured by the Coefficient of Variation (CV) of Revealed Technology Advantage (RTA) index, which is commonly used by previous studies (Soete, 1987; Cantwell & Vertova, 2004). The strength of RTA index is its ability to control inter-sectors and inter-countries differences in the propensity to patent (Cantwell, Gambardella, & Granstrand, 2004).

The Coefficient of Variation $\left(CV\right)$ of the RTA index across sectors for a given country is defined as the ratio between standard deviation and mean of RTA in j sectors in country/region i.

$$CV\left(RTA\right)=\frac{\sigma\left(RTA\right)}{\mu\left(RTA\right)}. \qquad (2)$$

The high value of *CV* indicates that the *RTA* distribution is highly concentrated in few specific fields of technology, which means that the degree of diversification is low. Reversely, when *CV* is low, the cross-sectoral distribution of *RTA* is widely dispersed. It means that the innovation activity is highly diversified across fields and not concentrated only in few activities rather than others.

RTA index itself measures the degree of specialization for a particular technological sector in a country/region. It is defined as the country/region share of patenting in that sector divided by its country/region share of patenting in all sectors, which are formed as follows:

$$RTA_{ij}=\frac{P_{ij}\Big/\sum_i P_{ij}}{\sum_j P_{ij}\Big/\sum_i\sum_j P_{ij}}, \qquad (3)$$

where P is the total number of patents of country i in sector j. The value greater than one suggests that a country/region is comparatively advantaged in the sector relative to other countries/regions in the same sector, while the value less than one represents a disadvantage position relative to others. As suggested by Cantwell and Vertova (2004), it is better to use the adjusted version of *RTA* index to retain the robustness considering the drawback of *RTA* itself which has a lower bound of zero, but, in contrast, it has no upper bound. Adjusted for *RTA* index is given by:

$$Adj\left(RTA_{ij}\right)=\frac{RTA_{ij}-1}{RTA_{ij}+1}+1. \qquad (4)$$

We calculated the RTA index based on EPO patenting applications for each country which are distributed into eight classes (e.g., patent with code C for chemistry sector and H for electricity sector) and 123 subclasses based on hierarchical International Patent Classification (IPC). High technological specialization means that patenting activities of a country are mostly concentrated into only electricity or chemistry sector, for instance.

As the income inequality variable, we use Gini index on household disposable income obtained from Eurostat. Gini index ranges from a minimum value of zero, represents perfect equality of household income to a maximum value of one, where only one household could generate the in-

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Table 1. List of variables

Variable names	Description	Source
	Measure of inequality	
Gini_eu	Gini index of inequality in country level	Eurostat
Top10_eu	The share of income own by the richest 10% (on a scale of 0 to 100)	Eurostat
	Measure of innovation	
Patent_pop	The number of patent application to the EPO per million population	Eurostat
	A measure of technological diversification	
Tech_div_RTA	Index of technological diversification, adopted from Revealed Technological Advantage index	Authors' calculation (based on patents application per technological fields obtained from Eurostat)
	Control variables	
GDPpcap	Real GDP per capita in Euro adjusted by Purchasing Power Parity	Eurostat
Popgrowth	The growth of total population	Eurostat
Gov_Exp	The ratio of government expenditure divided per GDP	PENN World Table
Openness	The ratio of country's total trade (export plus import) to GDP	PENN World Table
Edu_high	The population of working age with a tertiary education degree	Eurostat
Edu_low	The population of working age with lower than a secondary education degree	Eurostat
Unemploy	Unemployment rate	Eurostat

come. As a robustness check to measure top income inequality, in particular, we also use the top 10% income shares of the richest, which is also gathered from Eurostat.

As for the control variables, the data of GDP per capita, education attainment percentage, and unemployment rate are collected from Eurostat database, while the data of government expenditure and trade openness are drawn from PENN World Table.

To sum up, all the variables included in the model are demonstrated in Table 1

3. RESULTS AND DISCUSSIONS

In running panel data regression, one should consider choosing which model fits best into the case: either pooled OLS, fixed effect, or random effect model. Several tests then are conducted to find the appropriate model, including *F*-test, Breusch-Pagan Lagrange Multiplier (B-P LM) test, and Hausman test. The following table adopted from Park (2011) summarizes the choice of the model according to the results of the tests.

Table 2. A guide to choosing the fit model in panel data analysis

Source: Park (2011).

Condition	Fixed effect F-test	Random effect B-P LM test	Your selection
1	H0 is not rejected (no fixed effect)	H0 is not rejected (no random effect)	Pooled OLS
2	H0 is rejected (fixed effect)	H0 is not rejected (no random effect)	Fixed effect model
3	H0 is not rejected (no fixed effect)	H0 is rejected (random effect)	Random effect model
4	H0 is rejected (fixed effect)	H0 is rejected (random effect)	Hausman test is needed: fixed effect model if H0 is rejected; random effect model if H0 is not rejected

Both of null hypotheses in *F*-test and Breusch-Pagan Lagrange Multiplier (B-P LM) test are rejected suggesting that fixed effect and random effect models must be considered. This condition leads us to run a Hausman test. It tests whether the unique errors (idiosyncratic) are correlated with the regressors. If so, the fixed effect model fits better. This test suggests that fixed effects model is

the appropriate method of estimation rather than random effects model, since the null hypothesis is rejected.

Table 3 summarizes the results of a series of our fixed effect panel regression. In columns 1, 2 and 3, we regressed independent variables versus Gini index as the measure of income inequality. Meanwhile, in columns 4, 5, and 6, as a robustness check, we also considered top 10% income as the dependent variable to measure top income inequality, in particular. The results show positive and significant correlations between innovation and income inequality (columns 1 and 4), as well as between technological specialization and income inequality (columns 2, 3, 5, and 6).

Control variables indeed perform well. Both high-educated and low-educated workers level are negatively related to the dependent variable, confirming the theory about the skill-biased effect and the race between education and technological change. In other words, boosting the average level of education is important to restrain the increase of inequality, since it keeps the supply of high-skilled labor to complement new technology steady. Furthermore, unemployment rate variable, although not always significantly correlated, shows the positive direction as a sign that unemployment and inequality are closely related to each other and perhaps even the same issue. Trade openness and population growth give negative direction to the predicted variable, while GDP per capita shows the positive direction.

As stated in the previous section, to deal with the issue of reverse causation or simultaneity, we use time lag for patent per inhabitant as an explanatory variable. The use of time lag also means that innovation effects are delayed until they benefit by society. The strongest impact of innovation on income inequality is per-

Table 3. Results

Variable	(1) Gini EU 2003–2014	(2) Gini EU 2003–2014	(3) Gini EU 2003–2014	(4) Top 10% 2003–2014	(5) Top 10% 2003–2014	(6) Top 10% 2003–2014
Tech_spec (8 classes)	–	1.259*** (0.407)	–	–	1.270*** (0.337)	–
Tech_spec (123 subclasses)	–	–	0.346*** (0.133)	–	–	0.425*** (0.109)
Innovation	0.013** (0.006)	0.014** (0.006)	0.014** (0.006)	0.011** (0.005)	0.012** (0.005)	0.013*** (0.005)
Edu_high	–0.166*** (0.048)	–0.136*** (0.048)	–0.139*** (0.049)	–0.145*** (0.040)	–0.115*** (0.040)	–0.112*** (0.040)
Edu_low	–0.059 (0.039)	–0.038 (0.039)	–0.039 (0.040)	–0.074** (0.033)	–0.053 (0.033)	–0.049 (0.033)
Gov_Exp	–3.587 (4.372)	–6.201 (4.391)	–5.718 (4.406)	–3.073 (3.654)	–5.708 (3.643)	–5.694 (3.632)
Openness	–1.689*** (0.509)	–1.631*** (0.502)	–1.660*** (0.504)	–1.307*** (0.425)	–1.248*** (0.417)	–1.270*** (0.416)
GDPpcap	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000** (0.000)	0.000*** (0.000)	0.000** (0.000)
Popgrowth	–0.057*** (0.020)	–0.052** (0.020)	–0.054*** (0.020)	–0.042** (0.017)	–0.036** (0.017)	–0.038** (0.017)
Unemploy	0.047 (0.033)	0.057* (0.032)	0.053 (0.032)	0.001 (0.027)	0.011 (0.027)	0.009 (0.027)
R-square (within)	0.1332	0.1607	0.1528	0.1072	0.1485	0.1510
Group	28	28	28	28	28	28
N	329	329	329	329	329	329

Notes: Technological specialization (tech_spec) and innovation (innovation) are 3 years lagged. Panel data fixed effect regressions. Columns 1, 2, 3 use Gini index as a dependent variable, while columns 4, 5, 6 use top 10% of income shares as the dependent variable. *** p-value < 0.01, ** p-value < 0.05, *p-value < 0.1. Standard errors are in the brackets.

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formed when considering three years lagged. The result fades gradually when the lagged is increased along with the decrease of the *R*-square. Finally, the relationship is not significant when it exceeds ten years lagged. Those characteristics of the model indicate the temporary benefit of innovation. Patents that have been out of date are not beneficial anymore for the society. Reversely, when the lagged is shorter (i.e., 1 and 2 years), the correlation directly becomes insignificant. Indeed, it makes sense. It takes time for an invention to have an impact on the society. It might occur through two channels: either (1) through the increasing income of its inventors and the firm as the patent applicants, or (2) by the diffusion mechanism in which innovation spread to the market and subsequently benefits some people through 'Skill-Biased Technical Change'. Therefore, 1 or 2 years is too short for the invention to have an impact.

The reverse causality is supported by several recent studies such as Zweimüller (2000) and Tselios (2011). Inequality has an impact to innovation-based growth due to its effect on the structure and the dynamics of demand (Zweimüller, 2000). On the one hand, inequality may harm innovation through the market size effect. Unequal distribution means a small market size for innovative products as only small number of customer can afford them. On the other hand, inequality may be favorable for innovation through the price effect, means that higher 'willingness to pay' of rich people may attract innovators to increase their activities. Tselios (2011) then conducted empirical study to test the relationship, whether the price effect outweighs market size effect or vice versa. By providing dynamic panel model of European regions from 1995 to 2000, the author confirms that inequality favors innovation activity. Through unequal distribution, rich consumers tend to boost innovation activity, as they may have a very high willingness to pay for new expensive goods.

The findings confirm the first hypothesis that innovation increases income inequality. It is in line with the theory of skill-biased technical change. Innovation effect is not neutral in enhancing the whole of people income. Instead, it benefits partially, while harms others. Based on these findings, it confirms that middle-skilled jobs with routine tasks are the most vulnerable to the introduction of new technology. The explanation of this phenomenon is stressed well by Acemoglu and Autor (2011). Hypothetically, the income stagnation of those in the median occurs, because their tasks are substituted by automation. Thus, it dampens their wages relatively to the high-skilled labor. Reversely, innovation allows high-skilled labor whose tasks are more non-routine to increase their productivities. It then leads to the significant growth of their income. The study, thus, enriches the previous empirical research linking innovation and income inequality. Those include a study from Lee (2011), which conducts panel analysis in EU NUTS 1 region level and Antonelli and Gehringer (2013), which conduct the same analysis at the country level. Nevertheless, the results are contradictory. While study at the regional level found the positive relationship between them, in contrast, the country level study found the negative effect of innovation to inequality. It could be said that the result of this study opposes the finding from Antonelli and Gehringer (2013).

Secondly, this study also confirms the role of monopoly rent, which to some extent may increase the income inequality. It is reflected by the empirical finding that innovation affects the income shares of top 10% earners. This is in line with the Schumpeterian model from Aghion et al. (2015), which then was supported by their empirical study with U.S as the case study. According to their model, the increase of top income shares is caused by the increase of entrepreneurial income from innovators, which then compensates the decrease of wages income shares (i.e., employee salaries).

Thirdly, as suggested by columns 2, 3, 5 and 6 of Table 3, we found the significant and positive correlation between technological specialization and Gini index, as well as top 10% income shares. Technological specialization between 8 IPC classes and 123 subclasses matters to the increase of income inequality. Interestingly, the effect on the explanatory variable is stronger when innovation level variable is included in

Table 4. Findings as compared to previous studies

Authors (year)	Methods and case study	Result
Zweimüller (2000)	Mathematical model of income distribution, growth, and innovation	Inequality is an important factor of innovations and growth
Tselios (2011)	Fixed effect panel data model EU regions 1995–2000 (6 years)	Inequality increase the ability of innovation
Lee (2011)	Fixed effect panel data model EU regions 1996–2001 (6 years)	Innovation increases total income inequality
Antonelli and Gehringer (2013)	FGLS panel data model EU and OECD countries 1996–2011 (16 years)	Innovation decreases total income inequality
Aghion et al. (2015)	OLS with country and time dummies U.S. 1975–2010 (35 years)	Innovation increases top income inequality but not related to total income inequality
Hartmann et al. (2017)	Pooled OLS and fixed effect panel data models Countries worldwide 1996–2008 (12 years) and 1963–2008 (45 years)	Export product diversification (complexity) decreases income inequality
This study (2018)	Fixed effect panel data model EU countries 2003–2014 (12 years)	Innovation and technological specialization increase income inequality and top income inequality

the model. It suggests that technological specialization and innovation intertwine with each other in affecting the rising gap between rich and poor.

Thus, we confirm the hypothesis that technological specialization increases income inequality. It occurs, because technological specialization leads to inter-sector wage differentials. Sector in which innovation activities are concentrated tend to be able to produce better goods with lower cost compared to the rest. Since the sector is able to generate more money, demand for labor will also increase along with the increase of their income. The higher demand is especially for those high-skilled labor which can complement the innovation activities. The inter-sector wage differentials are then compounded by the rise of inequality within sector that cause total income inequality getting worse. The rise of inequality within sector is indicated by job polarization. High-skilled workers, on the one hand, benefit from the introduction of new technology. On the other hand, the middle-skilled workers are threatened. Innovations push them to shift their jobs into more unskilled tasks, which paid lower. A finding from Shim and Yang (2017) confirms that 'inter-industry wage differentials' are the key source of the differences level of job polarization across sectors.

High technological specialization means that the distribution of innovation activities is limited into few narrow sectors, while the rest lagged behind. For those reasons above, this will increase the wage differences between and within sector, and, consequently, it leads to the increase of total income inequality. In other words, this finding also suggests that technological diversification, as opposed to specialization, is better to restrain the increase of income inequality. Diversifying innovation activities into broad sectors will create the equal wages premium across sectors and thus inter-sector wage differential will be suppressed. Indeed, income gap within sectors will continually establish along with the presence of skill-biased technical change in all sectors. However, since the level of polarization is higher in more innovative sectors, diversifying innovations also to some extent will limit the job polarization within sectors. While Hartmann et al. (2017) found the link between trade and export specialization measured by the economic complexity index and income inequality, this study is the first which focuses on the specialization of technology or innovation activity.

To show the novelty and scientific contribution of this study, Table 4 presents the comparison with the previous findings.

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CONCLUSION

This study has presented the evidence linking innovation and income inequality in European countries in the period from 2003 to 2014. Our results found the positive and significant effect of innovation activity, which is measured by patent application on income inequality represented by Gini index, which confirms the mechanism of skill-biased technical changes. The most significant effect is found when we used 3 years of time lag in innovation activities as independent variable, suggesting that patent, as proxy of innovation, needs a time delay since its priority year to be noticeably benefited by society and affects the income distribution. This is in line with the study from Lee (2011), which conducts the similar model for EU between 1995 and 2001, but using NUTS 1 regions as the unit of analysis. We also found the positive and significant link of innovation and the shares of top 10% income, which confirms the mechanism of monopoly rent benefited by entrepreneurs as compared to the finding from Aghion et al. (2015), which provides empirical evidence from US state level. The findings confirm the hypothesis that innovation allows the top riches to earn much more prizes than the rest of the population. Overall, this study enriches the discourse by presenting that innovation activity at the country level, aside from region and state level, is also significant to the distribution of income.

The second finding in this article proposed the scientific novelty in the income inequality discourse as the first study, which considers the effect of technological specialization on income inequality. Many previous studies focus on how the level of innovation activities affects income inequality. None of them discuss the impact of the degree of its specialization. By using the Revealed Technological Advantage (RTA) index approach as the proxy of technological specialization, we found that countries tend to have higher level of income inequality if they concentrate innovation activities into few narrow sectors. The explanation is because concentrating innovation activities into specific sectors increases between sector wage differences, as the high technology sectors increase the demand for skilled labor. Furthermore, specialization also increases income inequality within sectors, especially for those high technology sectors. It means that although sectors with higher innovation activities could generate higher growth, the benefits are biased. The growth is only benefited by high-skilled labor, while those middle- and low-skilled labor tends to suffer, as currently demand for their skills is relatively lower.

This study presents the practical implication to be considered for formulating policies, particularly in linking innovation, inequality, and inclusive growth in the European Union. One of the missions of inclusive growth policy in the EU is to ensure the benefits of growth reach all parts of the society (European Commission, 2012). By 2020, the EU sets several targets including the increase of employment rate up to 75% and the reduction of 20 million people in or at risk of poverty. To achieve those targets, the EU proposes 'Innovation Union' initiative, which aims to forge better links between innovation and job creation by improving conditions and access to finance for research and innovation (European Commission, 2012). This strategy is thus expected to be able to create growth and jobs.

First of all, the study provides the evidence that, at the country level, innovation activities are strongly correlated with income inequality. EU has to consider these findings in translating 'Innovation Union' initiative into a series of practical strategies. Laissez-faire policies should not be continued. Otherwise, boosting the innovation activities, as suggested by the initiative, only leads to the worse income inequality. Further research has to be conducted in order to find out which innovation activities can lead to a more inclusive outcome, especially for those middle-skilled and low-skilled labor.

Related to the second finding, this study suggests that concentrating technology into few narrow sectors tend to increase inequality. Hence, while it is impossible to limit innovation activities, we would suggest that diversifying innovation into broad sectors would help the EU countries and regions to restrain the distribution gap between rich and poor. Countries should not only concentrate their innovation activities on their strength sectors, but also try to diversify their activities into sectors, which have long been regarded as their weakness. By doing so, inclusive growth will be achieved and income inequality will be restrained.

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