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Can innovation improve income inequality? Evidence from panel data

Siong Hook Law[a,*], N.A.M. Naseem[a], Wei Theng Lau[a], Irwan Trinugroho[b,c]

[a] School of Business and Economics, Universiti Putra Malaysia, Malaysia
[b] Faculty of Economics and Business, Universitas Sebelas Maret, Indonesia
[c] Center for FinTech and Banking, Universitas Sebelas Maret, Indonesia

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ABSTRACT

Income inequality is a source of social instability and armed conflict, which in turn are detrimental to economic development. This study examines the role of innovation in income inequality in twenty-three developed countries, using a panel mean group estimator that takes cross-sectional dependence into consideration. Three income inequality indicators are used: the Standardized World Income Inequality Database (SWIID), the University of Texas Inequality Project (UTIP), and the Estimated Household Income Inequality (EHII). The innovation indicators are patent applications and patents granted. The empirical results based on the common correlated effect mean group (CCEMG) reveal that innovation widens income inequality. We also investigate whether the innovation–income inequality nexus is subject to a country's level of globalization and financial development. The findings suggest that the interaction terms between innovation with these two variables have positive effects on income inequality, whereas innovation failed to reduce income inequality. Globalization and financial development are found to drive income inequality. The empirical results are robust to different income inequality and innovation measures as well as estimation techniques.

1. Introduction

The United Nations Development Program (UNDP), 2015 Report highlights that income inequality has increased in both advanced and developing countries. Rising income inequality can threaten social cohesion, hamper economic development and cause a recession (Brzezinski, 2018), and reduce the pace of human development. According to Deaton (2013) and Piketty (2014), over the past few decades, inequality has sharply increased in income worldwide and particularly in developed countries. Nevertheless, no consensus has been reached as to the main underlying factors behind this surge in income inequality. Therefore, to decrease vulnerability, sustain growth and reduce poverty, it is critical to address income inequality. In addition, Rhee and Kim (2018) argue that income inequality is an important factor in the emergence of banking crises. In recent years, evidence of the importance of innovation factors (knowledge production, patents, R&D, etc.) in promoting economic growth (Aghion et al., 2005; Galindo and Méndez, 2014; Hasan and Tucci, 2010) has increased. The same conclusion, however, cannot be drawn for income inequality because economic growth and income inequality are two different concepts. Researchers have not treated innovation and income inequality in great detail, thus, further attention needs to paid to the role of innovation in income inequality.

* Corresponding author.
E-mail address: lawsh@upm.edu.my (S.H. Law).

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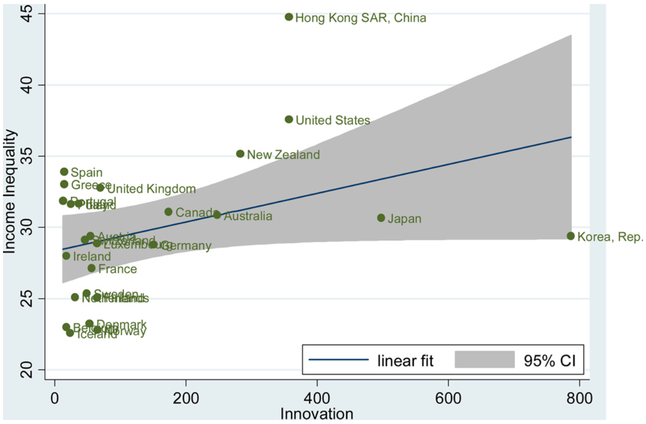

Fig. 1. Scatterplot of Income Inequality (SWIID) and Innovation (Total Patent Applications/Labor Force).

The World Economic Forum (2014) highlights that innovation activities have the potential to reduce income inequality. However, if innovation is able to reduce income gaps, why does the United States, a powerful force for innovation, have high income inequality? In this study, we argue that, in a developed country such as the US, innovation is certainly a factor. For instance, based on a list of the wealthiest individuals across the US in 2015 compiled by *Forbes* (Brown, 2015), eleven out of fifty are listed in a US patent as inventors, and many more manage or own firms that patent. More critically, income inequality in the US and other developed countries has a positive relationship with the number of patents (see Figs. 1, 3, 4, and 5). However, other countries, such as those in Scandinavia, have much less income inequality yet also have high innovation. Another example is China, which has the highest number of patents and has high income inequality, but Japan ranks second after China in terms of the number of patents but has less income inequality. According to Fukiharu (2013), using a simulation approach, when innovation emerges in country A under conditions of autarky, then, innovation tends to cause expansion in inequality. Although numerous studies have been conducted to analyze the determinants of income inequality, only a few deal with innovation as influencing income inequality. Because innovation drives productivity in developed economies (Aghion et al., 2019), and productivity drives the flows of real income, it is important to examine the role of innovation in income inequality.

This paper investigates the effect of innovation on income inequality in developed countries from 1990 to 2015. The rise of income inequality in many countries since 1985, particularly during the 2007–2008 global financial crisis, has prompted the current debate on the causes and consequences of higher inequality and its effects on future growth (see, e.g., Ostry et al., 2014). Much of research up to now has been descriptive in nature and motivated by inconsistent theoretical arguments. This study contributes to the literature in four respects. First, this study uses not only the number of patents as a proxy for innovation but the quality of innovation, which is measured by the number of patent applications to measure innovation activities. Second, this study tests the Schumpeterian hypothesis that the rate of technological change has a significant influence on narrowing income distribution. Because of the powerful effects of creative destruction, the rate of technological change engenders a reduction in wealth and rent inequality, which are highly skewed and, consequently, limit income inequality. Third, this study uses a time-series panel-data analysis that takes cross-sectional dependence into consideration in the model estimation. Lastly, we hypothesize that globalization and financial development play important roles in moderating the nexus between innovation and income inequality.

Globalization opens up a country's trade and financial markets and can help innovators to commercialize their products through exports as well as obtain external financing from international investors. However, Anderson (2009); Krugman (2008), and Stiglitz (2012) argue that the cause of expanded income inequality is innovation and globalization. Therefore, globalization is a vital mediator in influencing the innovation–income inequality nexus. Another potential mediator is financial development, which allows talented investors to access financing to ensure that innovation activities are carried out successfully. Thus, it tends to help talented innovators who do not have enough capital to achieve their goals and, in turn, reduces income inequality. Although these are all plausible conjecture, little, if any, direct empirical evidence so far has confirmed that globalization and financial development makes a difference in how innovation affects income inequality.

This paper represents a first step in providing such evidence, by testing the hypothesis that globalization and financial development play important roles in moderating the relationship between innovation and income inequality. For example, an increase in innovation activities, as captured by the standard indicators of innovation, might not narrow income inequality. For example, income inequality tends to increase during a wave of globalization because higher demand leads to higher wages for highly skilled workers. The low-skilled workers are neglected or even receive lower wages, which widens the income inequality gap. Weak financial systems tend to hinder the development of the banking sector or capital market in channeling funds from sectors with a surplus to those with a deficit, which may hamper innovation activities.

This paper is organized as follows: Section 2 reviews the literature and Section 3 lays out the empirical model and the econometric method, while Section 4 discusses the data. Section 5 contains a discussion of the empirical findings, Section 6 contains robustness checks, and, finally, Section 7 provides a summary and conclusions.

2. Literature review

The positive relation between income inequality and economic growth has spawned research into the determinants of income inequality. The literature suggests a range of factors that might account for the differences in the levels of income inequality across countries. Numerous studies have assessed the causes of income inequality, especially those on the effects of slow economic growth and social unbalance.[1] Recently, the literature has concentrated on technological change or innovation as a cause of income inequality. Antonelli and Gehringer (2017) argue that the slowing pace of technological change is another source of income inequality. They test the Schumpeterian hypothesis that the rate of technological change has a significant influence on reducing income distribution. Because of the powerful effects of creative destruction, the rate of technological change engenders a reduction in wealth and rent inequality, which are highly skewed and, consequently, limit income inequality. They test this hypothesis in an empirical exercise by performing quantile regressions with a large dataset on advanced and industrializing economies. The inequality-diminishing effect of technological change holds along the entire income inequality distribution but has larger effects in countries where the concentration of wealth and, consequently, income asymmetry are stronger.

Although the slowing pace of technological change or innovation is one source of income inequality, in another study, Perera-Tallo (2017) argues that increasing income inequality is due to biased technological change. He presents a growth model in which technological change increases the income share of reproducible factors at the expense of nonreproducible ones. Agents are heterogeneous in wealth and preferences, indicating that the savings rate increases with wealth. As a result, assets (reproducible factor) are distributed less equally than raw labor (nonreproducible factor). This suggests that technological change increases the share of the less-equally distributed factor, increasing inequality along a permanent growth path. When reproducible factors and the state of know-how are low, adopting new technologies is not profitable, and learning-by-doing and technological change stop, which could increase unproductive activities. Pouresmaeilia et al. (2018) reveal that innovation plays an important role in mediating the knowledge management system and performance nexus. Samargandi (2018) indicates that, in the Middle East and North African region, innovation is found to be an important factor in accelerating labor productivity.

Some researchers disagree with the Schumpeterian hypothesis, in which the rate of technological change significantly influences reductions in income inequality. Kinugasa (1998) investigates the structure of firm productivity and the Schumpeterian hypothesis using data on Japanese trunk route airlines over the period 1977–1993. Empirical tests of this hypothesis have traditionally examined the relationship between some measure of innovative activity and firm size. The rate of technical change is used to measure the innovative activity using some innovative inputs and outputs. The total factor productivity (TFP) can be decomposed into the technical change and changes in the economies of scale, thus the shift in the cost function is associated with these two changes. The Schumpeterian hypothesis is tested with the technical change, and the empirical results rejected this hypothesis.

Cuaresma et al. (2013) demonstrate that although research exists on the influential role of technological change in influencing income inequality, education or human capital also plays an important role in reducing income inequality and income convergence. Shahpari and Davoudi (2014) argue that increasing human capital can reduce income inequality and, hence, make income distribution fairer. To ensure the success of innovation activities, better human capital is a crucial component in how innovation influences income inequality across countries. The wider the distribution of human capital is, the greater is the chance of fostering the pace of technological change and reducing income inequality. Campos et al. (2016) evaluate the impact of education on income inequality between ethnic minorities and the Han ethnic majority in China using data from the China Health and Nutrition Survey from 1993 to 2011. An instrumental variable approach using two institutional changes is applied to address the endogeneity of education in income equations for various subsamples. They use an interaction term between the ethnic minority status and the number of years of education. Their findings show specific returns to education for ethnic minorities, which implies that a portion of the income gap can be overcome with additional education.

Using the dataset on human capital inequality for 146 countries from 1950 to 2010, Castelló-Climenta and Doménecha (2014) find that despite a large reduction in human capital inequality around the world, inequality in the distribution of income has hardly changed. In many regions, the Gini income coefficient in 2005 was very similar to that in 1960. Therefore, improvements in education are an insufficient condition for reducing income inequality, even though they significantly improve living standards for people at the bottom of the income distribution. They demonstrate that increasing returns to education and exogenous forces, such as skills-biased technological progress or globalization, have offset the effects of the decline in education inequality, therefore explaining the low correlation between the changes in income and education inequality.

According to growth theory, human capital inequality is one such determinant. Improvements in the health and education of people are central to the development process. Clearly, people place a high value on the health and education of their family members and themselves, and thus their improvement must be a goal of development. At the same time, the health and education of an individual have an important effect on that individual's ability to produce. A healthier, better-educated person can produce more, and this improved productivity is rewarded in the labor market. Abrigo et al. (2018) demonstrate that human capital investment has a positive effect on labor productivity and, hence, output. The positive effect is stronger for poorer households and, hence, beneficial for equity.

Yang and Qiu (2016) evaluate the effects of innate ability, compulsory education (grades 1–9), and noncompulsory education (grades 10–12 and higher education) on inequality and intergenerational mobility of income, by constructing a four-period

[1] Brada (2013) reviews the literature on labor's share of national income in developed and developing countries. He finds that the decline in labor's share includes technical progress, globalization, and a decline in labor's bargaining power. However, none of these explanations accounts for both the rise and the decline of labor's share over time and for a similar pattern in developed and developing countries.

overlapping-generation model. Their empirical findings reveal that innate ability and family investment in early education play important roles in explaining income inequality and intergenerational income mobility. Although children from the wealthiest families are only 1.36 times “smarter” that those from the poorest, the gap in human capital expands to 2.35 at the end of compulsory education and to 2.89 at the end of noncompulsory education. One important reason for the increase is that poor families invest less in children’s early education than do wealthy families; therefore, their children attend lower-quality schools, which leads them to be much less likely to participate in higher education. By simulating policy experiments for different types of government education expenditure, they find that direct subsidies to impoverished parents are the most efficient and effective policy for mitigating the budget constraints for these families with regard to investment in the early education of their children.

Another strand of the literature highlights the role of institutions in reducing income inequality. According to Chong and Calderon (2000), better institutional quality has been identified as an important determinant in reducing income inequality. It has been often linked to an increase in efficiency, where good institutional quality is the common characteristic shared by countries that experience sustainable growth and economic stability. The characteristic of good institutional quality should include effective government with a commitment to economic development, a well-functioning parliament, good contract enforcement, and investor protection. Adelman et al. (1992) find that institutional quality is the most important characteristic that distinguishes the successful countries from the less successful. Moreover, classical theory stressed that it is the interaction of resources, technology, and comparative advantage with institutional conditions and institutional change that determines the development pattern of an economy. This signifies the importance of good institutional quality. Therefore, institutional quality may have a corrective effect on income inequality.

Using a panel vector autoregressive (VAR) approach, Chong and Gradstein (2007) point out that institutional quality is significantly correlated with income inequality. In addition, income inequality is found to be correlated with low institutional quality, which indicates the reinforcing quality between institutional quality and income inequality. The dynamic relationship in their study suggests that higher institutional quality is linked to improvement in the distribution of income, thus indicating that a more equal distribution of income is linked to higher institutional quality.[2] They point out that the direction of causality from income inequality to institutional quality appears to dominate reverse causality, which explains why better institutional quality may lead to a more equal distribution of income. Hence, this may explain why countries with full awareness of the need to pursue dramatic institutional reforms have failed to do so.

Numerous studies have also assessed the role of inflation in influencing income inequality. Nantob (2015) argues that higher inflation is associated with higher income inequality. As inflation rises, so does inequality, reaching a maximum at an inflation rate of about 109 percent, and then starts decreasing again. Cysne et al. (2005) also investigate the effect of inflation on the Gini coefficient of income distribution by developing a simplified model based on a shopping-time rationale. They also find a positive link between inflation and income inequality. The relationship between income inequality and crime also has received attention in the literature. For example, Goh et al. (2018) investigate the effect of income inequality on crime using a dynamic panel system generalized method of moments (GMM) model for the period 1989–2012. They also evaluate whether institutional quality plays a role in moderating the relationship between income inequality and crime. The empirical results reveal that income inequality is positively associated with crime. Better institutional quality tends to have a negative moderating effect on the relationship between the two variables.

Using a panel fixed-effects model for a sample of 121 countries covering 1975–2005, de Haan and Sturm (2017) investigate how financial development, financial liberalization, and banking crises are related to income inequality. Their empirical findings suggest that all finance variables increase income inequality. The level of financial development and the quality of political institutions condition the impact of financial liberalization on inequality. However, the quality of economic institutions has no contingent impact of financial liberalization on inequality. Their main findings are robust to random effects, cross-country regressions, and legal origin as instruments for financial development.

With respect to financial liberalization policies, Agnello et al. (2012) evaluate the effect of financial reforms on income inequality. Using a panel of sixty-two countries from 1973 to 2005, they find that the elimination of policies on directed credit and excessively high reserve requirements and improvements in the securities market reduce inequality. This finding is in line with McKinnon (1989) that financial reform policies have a positive impact on financial development and hence, reduce income inequality. Johansson and Wang (2014) also assess the role of financial policies in income inequality using a cross-country analysis. They demonstrate that financial repression tends to increase income inequality. They also find that credit controls and entry barriers in the banking sector are the two most important financial policies influencing inequality. In addition, per capita growth in the gross domestic product (GDP) and urbanization are two important factors that might mitigate income inequality. Their finding highlights that, in rapidly developing countries such as China, the income inequality issue should not be neglected. Hou et al. (2018) point out that if it wishes to reduce income inequality, the Chinese government should help to promote equity financing and decrease excessive speculation on the stock market. Hua and Yin (2017) conduct a Gini decomposition analysis and illustrate that rural income inequality would also be reduced if they did not migrate and worked closer to home.

Although the link between financial development and income inequality has a linear relationship, the literature also shows the nonlinear relationship between these two variables. Kim and Lin (2011) reveal that the effect of financial development on income inequality is contingent on the level of financial development, where the benefits of financial depth occur only if the country has achieved a threshold level of financial development. Below that threshold, financial development counteracts income inequality. Therefore, a minimum level of financial development is a necessary precondition for achieving reduction in income inequality through

[2] Data obtained from datasets in Deininger and Squire (1996) and Kaufman et al. (2003).

financial development. Tan and Law (2012) also investigate the dynamics in the finance-inequality nexus in thirty-five developing countries, using two datasets on income inequality: the University of Texas Inequality Project (UTIP) and the Standardized World Income Inequality Database (SWIID). The empirical results using dynamic panel GMM reveal the nonlinear U-shaped relationship between financial deepening and income distribution, which implies a narrowing of the income-inequality gap at the early stage of financial development in the countries. This improvement, however, will be sustainable dynamically only below a certain threshold. Further deepening above that level has a reverse effect, which worsens income inequality. Park and Shin (2017) also find that financial development contributes to lower inequality up to a point, but as financial development proceeds further, it contributes to higher inequality. In terms of microfinance, Selvaraj et al. (2018) demonstrate that the number of loans per microcredit office has a significantly positive effect on a lower income group headcount.

In terms of globalization and income inequality, Asteriou et al. (2014) examine the relationship using panel-data techniques for the twenty-seven member countries of the European Union (EU-27) over the period 1995–2009. The analysis is also performed with subgroups of countries in the EU-27, such as the core, periphery, high-technology, and new member states. The empirical results suggest that trade openness has an equalizing effect, whereas financial globalization through foreign direct investment (FDI), capital account openness, and stock market capitalization has been the driving force of inequality in the EU-27 since 1995. The highest contribution to inequality stems from FDI. Although the trade impact remained robust, disparities were observed in the financial globalization effects within a certain group or among country groups. The 2007–2008 global financial crisis led to a significant rise in inequality only in the EU periphery and among the new member states. Bahmani-Oskooee and Ardakani (2020) find that the Gini coefficient responds to income volatility in an asymmetric manner. They find short-run asymmetric effects in almost all forty-two developed and emerging countries, asymmetric short-run effects in twenty countries, and long-run asymmetric effects in twenty-one countries.

Bergh and Nilsson (2010) examine whether the KOF Index of Globalization and the Economic Freedom Index of the Fraser Institute are related to within-country income inequality. The income inequality measure they use is the SWIID. They use panel data covering around eighty countries from 1970 to 2005. The findings demonstrate that freedom to trade internationally is robustly related to inequality, also when adding several control variables and controlling for potential endogeneity using GMM. Social globalization and deregulation are also linked to inequality. Reforms to achieve economic freedom seem to increase inequality mainly in rich countries, and social globalization is more important in less developed countries. Mah (2013) points out that trade liberalization has led to higher income inequality but has mixed evidence relating to the effect of FDI inflows on income inequality in China. At the same time, Adams and Klobodu (2017) suggest that FDI increases income inequality in both the short and the long run in sub-Saharan African countries. Remittances, external debt, and aid flows, however, do not have a robust impact on income inequality. Therefore, different findings emerge on the effects of globalization and openness on income inequality, subject to the countries used in the analysis.

Overall, these strands of the literature highlight that many factors affect income inequality. However, no single study exists that adequately addresses the role of innovation in income inequality. Further, very little research evaluates the interaction effect between innovation with globalization and financial development. Our work contributes to the literature on these aspects.

3. Empirical model and methodology

The Schumpeterian growth model stated that growth results from quality-improving innovations can be made in each sector by either the incumbent in the sector or potential entrants. Facilitating innovation or entry increases the entrepreneurial share of income and spurs social mobility through creative destruction as employees' children can more easily become business owners and vice versa. In particular, this model predicts that innovation by entrants and incumbents increases income inequality. To examine the effect of innovation on income inequality, this study uses the following income inequality equation:

$$IIE_{it} = \alpha + \beta_1 INNO_{it} + \beta_2 X_{it} + u_{it} \tag{1}$$

$$u_{it} = \tau_i^{'} f_t + \varepsilon_{it}$$

where *IIE* is income inequality, *INNO* is a variable for innovation, *X* is a vector of other conditional variables that affect income inequality, *i* is the country, *t* is the time, u_{it} is an error term, and f_t is a vector of unobserved common shocks, which can be stationary or nonstationary (Kapetanios et al., 2011) and can be serially correlated and possibly related to other explanatory variables. This factor contains global shocks and financial crises as well as local technology spillover effects that influence innovation in all countries but to different degrees. It is also assumed that ε_{jt} is serially correlated, weakly independent across countries, and uncorrelated with regressors and unobserved common shocks.

The group of conditional variables (*Z*) consists of real GDP per capita (*RGDPPC*), human capital (*HC*), inflation (*INF*), and institutions (*INS*). Globalization (*GLOB*) and financial development (*FD*) are used not only as conditional variables but also as mediating variables (*X*). All the variables are transformed into the natural logarithm. We controlled for *RGDPPC* because it has been found to reduce income inequality by, for instance, Yang and Greaney (2017). Human capital is included in the specification because it has been found to reduce income inequality (Campos et al., 2016; Yang and Qiu, 2016). Inflation is included because greater inflation tends to increase the income–inequality gap (Menna and Tirelli, 2017; Nantob, 2015). Institutions are included because better institutions tend to reduce income inequality (Chong and Gradstein, 2007; Lin and Fu, 2016). We also controlled for globalization because it has been found to increase income inequality (Bergh and Nilsson, 2010; Mah, 2013). Financial development is also included in the model specification because this variable has been found to affect income inequality (De Haan and Sturm, 2017; Tan and Law, 2013).

3.1. Endogeneity test

A potential endogeneity problem stems from reverse causality between income inequality and innovation, so we perform a Durbin-Wu-Hausman test to detect endogeneity. The reverse causality is likely because people in a country with low inequality (due to transfers, where government payments to individuals through social programs such as welfare, student grants, and even Social Security) may have low motivation to innovate. Consider again the following model:

$$IIE_{it} = \alpha + \beta_1 INNO_{it} + \beta_2 X_{it} + \beta_3 RGDPPC_{it} + \beta_4 HC_{it} + \beta_5 INS_{it} + \beta_6 INF_{it} + \varepsilon_{it} \tag{2}$$

where X is a vector of globalization and financial development variables, and *INNO* is the variable suspected to be endogenous. The goal is to construct instruments that are correlated with innovation but not with income inequality.

We employ lagged innovation and R&D expenditure over GDP as instruments for innovation. Both the theoretical and empirical literature reveal that investment in R&D is crucial for economic growth. Many models (Aghion and Howitt, 1992; Grossman and Helpman, 1991; Romer, 1990) theoretically illustrate the function of R&D as a growth engine and highlight why government must play a role in achieving the optimal level of R&D. According to Baker et al. (2017), R&D expenditure is highly correlated with innovation. Because innovation is a function of creative activity, countries with an environment conducive to such activity, in both the public and private sectors, are a priori more likely to innovate successfully. Porter and Stern (2000) employ data on patents and the R&D expenditure in sixteen member countries of the Organization for Economic Cooperation and Development to estimate the knowledge and output production functions. Their findings indicate that both variables increase the ideas production function and aggregate output. Rodríguez-Pose and Crescenzi (2008) analyze the link between investment in R&D, patents, and economic growth in Europe. They find that R&D investment is more conducive to economic growth because of its impact on performance in both local and neighboring regions. Kim and Park (2018) also point out that R&D growth is a significant source of TFP growth.

The basic idea behind the test is as follows:

$$IIE_{it} = \alpha + \beta_1 INNO_{it} + \beta_2 X_{it} + \beta_3 RGDPPC_{it} + \beta_4 HC + \beta_5 INS_{it} + \beta_6 INF_{it} + \varepsilon_{it} \tag{2a}$$

$$INNO_{it} = \pi_1 X_{it} + \pi_2 RGDPPC_{it} + \pi_3 HC_{it} + \pi_4 INS_{it} + \pi_5 INF_{it} + v_{it} \tag{2b}$$

where Eq. (2a) is a structural equation, and Eq. (2b) is a reduced-form equation, respectively. We can confirm that *INNO* is correlated with ε_{it} only if v_{it} is correlated with ε_{it}. Further, let

$\varepsilon_{it} = \delta\, v_{it} + e1$

Then ε_{it} and v_{it} are correlated only if $\delta = 0$. Thus, consider

$$IIE_{it} = \alpha + \beta_1 INNO_{it} + \beta_2 X_{it} + \beta_3 RGDPPC_{it} + \beta_4 HC_{it} + \beta_5 INS_{it} + \beta_6 INF_{it} + \delta v_{it} + e1 \tag{3}$$

Then, test H0: $\delta = 0$. If we reject H0, then we conclude that *INNO* is endogenous because ε_{it} and v_{it} are correlated. The empirical results of the endogeneity test are reported in the Appendix.

3.2. Interaction effect model

To examine the moderating roles of globalization and financial development with innovation in influencing income inequality, Eq. (2) is extended to include the interaction term between these respective variables in the model specification as follows:

$$IIE_{it} = \alpha + \beta_1 INNO_{it} + \beta_2 GLOB_{it} + \beta_3 (INNO\ x\ GLOB)_{it} + \beta_4 Z_{it} + \mu_{it} \tag{4}$$

$$IIE_{it} = \alpha + \delta_1 INNO_{it} + \delta_2 FD_{it} + \delta_3 (INNO\ x\ FD)_{it} + \delta_4 Z_{it} + \mu_{it} \tag{5}$$

Eqs. (4)–(5) provide the basis for the empirical model by interacting between innovation and these two mediators or indirect effects in influencing income inequality. Z are control variables as shown in Eq. (2), namely *RGDPPC, HC, INS*, and *INF*. According to Brambor et al. (2006), it is inappropriate to interpret individual term β_1 and β_2 in Eq. (4) if the model contains an interaction term. The coefficient of β_1 on *INNO* captures only the effect of innovation on income inequality when *GLOB* is zero. Similarity, β_2 captures only the effect of *GLOB* on income distribution when *INNO* does not exist. Therefore, it is incorrect to indicate that negative and significant coefficients of β_1 and β_2, imply that an increase in innovation (globalization) is expected to lead to reduce income inequality in Eq. (4). Thus, β_1 and β_2 are not highlighted in Eq. (4). However, *GLOB* as the mediator is expected to buffer the effect of innovation on income inequality, thus, whether β_3 is expected to be marginally positive or negative depends on the influence of innovation on income inequality. In Eq. (4), changes in income inequality due to changes in innovation (marginal effect) from globalization are represented as follows:

$$\frac{\partial IIE}{\partial INNO} = \beta_1 + \beta_3 GLOB \tag{6}$$

The marginal effect of Eq. (5) where the moderating variable is financial development is as follows:

$$\frac{\partial IIE}{\partial INNO} = \delta_1 + \delta_3 FD \tag{7}$$

Eq.s (6) and (7) highlight the changes in *IIE* due to innovation, subject to $\beta_1$andβ_3 for globalization and δ_1 and δ_3 for financial development.

If the interaction term (*INNO* x *X*), where *X* = *GLOB* and *FD,* is negative and significantly related to income inequality, then this supports the view that *INNO* has a negative effect on income inequality only if *X* has achieved a certain minimum level. At the margin, the total effect of reducing income inequality due to *X* can be calculated by examining the partial derivative of income inequality with respect to *INNO* in Eq.s (6) and (7). The marginal effect asserts that the effect of a change in *IIE* on innovation depends on the value of the two mediators (globalization and financial development). As suggested by Brambor et al. (2006), we must calculate the substantively meaningful marginal effect of innovation on *IIE* by calculating the new standard error.[3]

For instance, in Eq. (4), where globalization is used as interaction term with innovation, the marginal effect is $\frac{\partial IIE}{\partial INNO} = \beta_1 + \beta_3 GLOB$. Using the covariance matrix, the variance, σ^2 (i.e., or standard error, σ), is calculated as:

$$\sigma^2_{\frac{\partial IIE}{\partial INNO}} = Var(\widehat{\beta}_1) + GLOB^2\ Var(\widehat{\beta}_3) + 2GLOB\left[Cov(\widehat{\beta}_1\widehat{\beta}_3)\right] \tag{8}$$

where *Var* and *Cov* are the variance and covariance matrix of Eq. (4). $\widehat{\beta}_1$ and $\widehat{\beta}_3$ are the estimated coefficients of Eq. (4). The marginal effect must be calculated at various values of *GLOB*, from minimal globalization to maximum globalization in the sample.

The same procedures apply to Eq. (7), where the interaction terms are between financial development (*FD* = *PRI*) and innovation. $\widehat{\delta}_1$ and $\widehat{\delta}_3$ are the estimated coefficients of Eq. (7).

$$\sigma^2_{\frac{\partial IIE}{\partial INNO}} = Var(\widehat{\delta}_1) + PRI^2\,Var(\widehat{\delta}_3) + 2PRI\left[Cov(\widehat{\delta}_1\widehat{\delta}_3)\right] \tag{9}$$

The results of the marginal effect are presented graphically to illustrate the significance of both mediators and also the significance of the marginal effect.

3.3. Econometric methodology

This study uses the common correlated effects (CCE) estimator developed by Pesaran (2006) to estimate the parameters. Two features of this model are worth noting. The model permits the vector of the slope coefficients, β_i, to be heterogeneous across countries. Additionally, the country-specific fixed effects, α, and country-specific deterministic trends, $d_i t$, allow a heterogeneous rate for depreciation, growth of labor, and technological progress across countries. Another advantage of nonstationary panel data with these two country-specific determinants, α_j and $d_j t$, is that they are proxies for unobserved factors, and thus the heterogeneous panel-data approach eliminates the need to search for this type of quantitative variable, which is necessary with cross-sectional and homogeneous panel-data methods.

To eliminate the cross-sectional dependence (CD) introduced by unobserved factors, we use the CCE estimator developed by Pesaran (2006) to investigate the role of innovation in income inequality. The CCE estimator uses Eq. (1) to augment the ordinary least squares regression with the cross-sectional average of the dependent and independent variables as proxies for unobserved common factors.

There are two kinds of the CCE estimators. If the slope coefficients β_i are the same across countries, the CCE pooled (CCEP) estimator produces efficient estimations by pooling observations over the cross-sectional units. In contrast, the slope coefficients can differ across an individual CCEMG estimator, which is used in this study. This estimator is constructed by taking a simple average of each country's CCE estimator:

$$\widehat{\beta}_{CCEMG} = \frac{1}{N}\sum_{i=1}^{N}\widehat{\beta}_i \tag{10}$$

Using the CCE estimator has several advantages. Unlike the cross-sectional and homogeneous panel methodologies, the need to find proxies for these factors is relaxed, as the country-specific determinants, α_i and $d_i t$, capture both the global and the local unobserved factors as well as any omitted variables. In addition, the CCE estimation approach uses annual data, rather than a five-year average, as in most economic growth literature, to eliminate the business cycles with the GMM.

4. Data

This study focuses on developed countries because they have more innovation than developing countries.[4] Three datasets are used to estimate the models corresponding to the three different sources of income inequality, or Gini coefficient. When income inequality is measured with the SWIID (Solt, 2014), this study uses the dataset on twenty-three developed countries (see Appendix Table A1), and

[3] Numerous studies have employed the method in Brambor et al. (2005) to calculate the new standard error. For instance, Balli et al. (2018); Kingsley et al. (2017); Law and Azman-Saini (2012), and Law et al. (2018).

[4] Initially, we had 26 sample countries, but we dropped 3 because they were outliers. The list of countries is presented in Table 1.

Table 1
Descriptive Statistics.

Variables	Unit of measurement	Mean	Std. Dev.	Min.	Max.
Income Inequality (Gini)					
SWIID	Percent	29.52	5.07	17.37	52.98
UTIP	Theil's T statistic	0.022	0.014	0.003	0.072
EHII	Percent	36.83	3.33	28.64	45.94
Innovation					
Total patent applications/labor	Ratio (in 100,000 workers)	137.57	153.17	2.81	786.88
Total patents granted/labor	Ratio (in 100,000 workers)	62.08	65.41	0.93	482.09
Inflation	Percent	4.00	22.62	−4.48	555.38
Human capital	Life expectancy, scale (1–100)	78.63	2.32	70.59	83.83
Real GDP per capita	US$ (2010 constant prices)	40,661.20	18,467.19	5,509.90	111,968.00
Globalization	Scale 1–100	77.55	10.30	41.16	90.67
Private sector credit	% of GDP	107.25	43.57	12.89	312.12
Institutions	Scale 1–50	42.19	4.66	24.72	49.17

List of countries: Australia, Austria, Belgium, Canada, Finland, France, Germany, Greece, Hong Kong, Ireland, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Spain, Sweden, Switzerland, the United States, and the United Kingdom.

Table 2
Correlation.

	Gini-SWIID	Gini-UTIP	Patent applications/labor	Patents granted/labor	Inflation	*HC*	*RGDPPC*	*GLOB*	*PSC*	*INS*
Gini-SWIID	1.0000									
Gini-UTIP	0.6787	1.0000								
Patent applications/labor	0.0407	0.0979	1.0000							
Patents granted/labor	0.0258	0.1212	0.8550	1.0000						
Inflation	0.0400	0.0597	−0.1312	−0.1060	1.0000					
HC	−0.1332	−0.1459	0.1902	0.1025	−0.2171	1.0000				
RGDPPC	−0.378	−0.3225	0.3357	0.2922	−0.1354	0.3816	1.0000			
GLOB	0.1201	0.1807	0.0899	0.1154	−0.0356	0.0256	0.0978	1.0000		
PSC	0.2814	0.2256	0.3313	0.2197	−0.1268	0.4829	0.2138	0.1773	1.0000	
INS	−0.517	−0.4232	0.3020	0.3052	−0.1495	0.0097	0.5343	0.0726	0.1192	1.0000

Note: HC = human capital; *RGDPPC* = real GDP per capita; *GLOB* = globalization; *PSC* = private sector credit; *INS* = institutions.

the sample period covers from 1990 to 2013;[5] when the measurement employs UTIP (Galbraith and Kum, 2005), we use the dataset on twenty-three developed countries, and the sample period covers from 1990 to 2015;[6] and when it is measured with the EHII, the sample consists of twenty-three developed countries, and the sample period is from 1990 to 2008.[7]

Data on innovation are measured by total patent application per worker and total patents granted per worker extracted from the World Intellectual Property Organization. The number of patent applications and patents granted as a measurement of innovation is widely used by researchers, such as Bottazzi and Peri (2003); Jaffe (1986); Tebaldi and Elmslie (2013), and Wang (2013). The labor force data come from the World Bank's World Development Indicators (WDI). Human capital is proxied by life expectancy (World Development indicators, WDI), a variable used in numerous studies, including Azman-Saini et al. (2010); Bloom and Sachs (1998); Kokotović (2016), and Law and Singh (2014). The importance of human capital through educational attainment is correlated with economic development in Barro (1991) and Lucas (1988). A larger and well-educated labor force also implies a larger number of more skilled workers and a greater ability to absorb advanced technology, thus the level and distribution of educational attainment also affect social outcomes, such as the education of children, together with income distribution.

Globalization is obtained from the KOF database, which measures the economic, political, and social dimensions of globalization. The data are obtained from the KOF Swiss Economic Institute. Financial development, measured by private sector credit over GDP,

[5] Solt (2014) used various techniques to estimate the ratios between different types of Gini coefficients—relying more on information about the ratio in the same country nearby in time—to increase the number of comparable observations.

[6] The dataset in Galbraith and Kum (2005) also provides comparable and consistent measures across space and over time that the earlier dataset of Deininger and Squire (1996) does not. It is based on the inequality of manufacturing wages obtained from the data collected by the United Nations Industrial Development Organization (UNIDO). The current UTIP-UNIDO database of industrial pay inequality consists of 4,054 country annual observations that cover 167 countries.

[7] The Estimated Household Income Inequality (EHII) database of estimated gross household income inequality has 3,871 observations of 149 countries. Numerous measures and estimates obtained from other works are compared with the EHII that indicate the general reliability of the trends, and coherently though imperfectly, the level of the inequality estimator is portrayed in the EHII surveys (Galbraith et al., 2014).

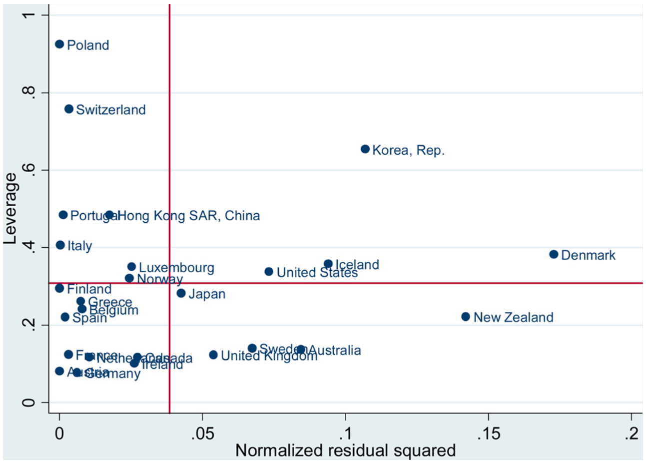

Fig. 2. Scatterplot of Leverage and Residual Squared.

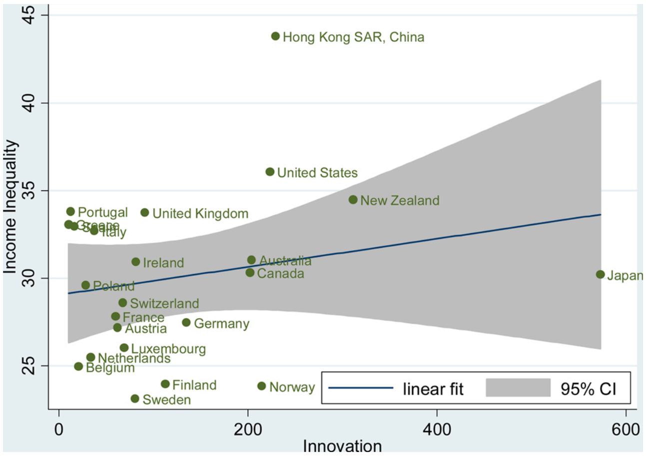

Fig. 3. Scatterplot after Dropping the Outlier Countries.

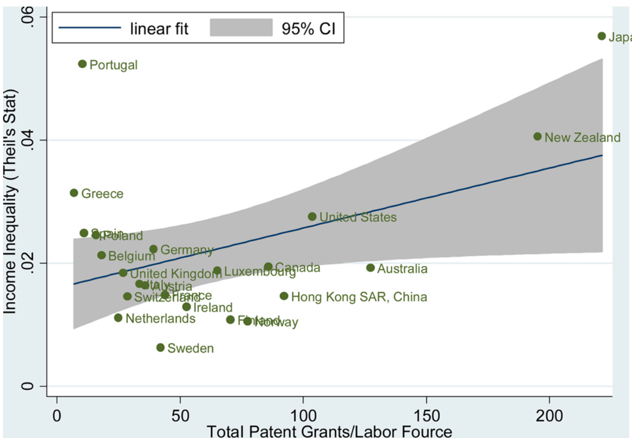

Fig. 4. Scatterplot of Income Inequality (UTIP) and Innovation (Total Patent Applications/Labor Force).

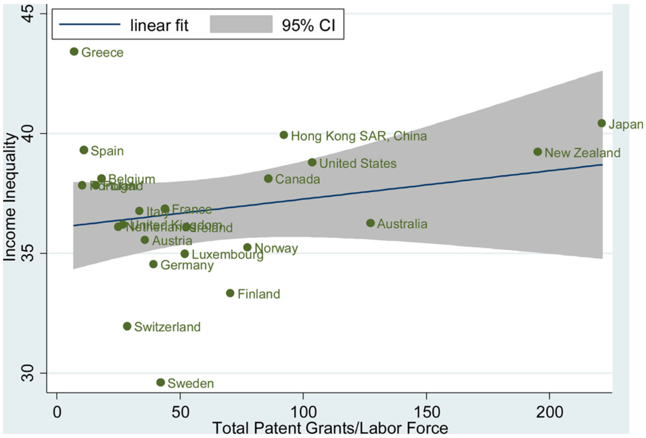

Fig. 5. Scatterplot of Income Inequality (EHII) and Innovation (Total Patent Applications/Labor Force).

Table 3
Variance Inflation Factor in Multicollinearity Test (Dependent variable: Gini = SWIID).

	Innovation = Total patent applications/labor force		Innovation = Total patents granted/labor	
Variables	Mean	Std. Dev.	Mean	Std. Dev.
Innovation	1.12	0.8890	1.25	0.7975
Inflation	1.20	0.8321	1.30	0.7702
Human capital	2.05	0.4881	2.40	0.4171
Real GDP per capita	2.71	0.3688	2.77	0.3611
Globalization	1.04	0.9584	1.16	0.8631
Private sector credit	1.63	0.6136	1.71	0.5847
Institutions	1.97	0.5079	2.03	0.4936
Mean VIF	1.68		1.80	

RGDPPC, and inflation are obtained from WDI. Institutional quality is obtained from the *International Country Risk Guide* by adding up five institutional indicators: corruption, law and order, bureaucratic quality, democracy and accountability, and government stability (Political Risk Services). All five indicators are scaled by a factor of ten. This implies that for a country with perfect institutions the maximum value is fifty. A higher value means better institutions.

Table 1 lists the descriptive statistics of the variables and the unit of measurement based on level data with logarithm. The standard deviations for two innovation variables and inflation are higher than their means, which indicates that the deviation for these variables is large. Table 2 reports the correlations among the variables, in which innovation, inflation, globalization, and financial development have a positive correlation with income inequality. Aghion et al. (2019) also find a positive correlation between the measures of innovation and income inequality. However, income distribution has a negative relationship with human capital, *RGDPPC*, and institutions.

Fig. 1 is a scatterplot of the relationship between innovation (total patent applications) and income inequality that shows a positive relationship. Because a few countries might be outliers, we use the Cook's Distance outlier test. The result indicates that three countries—Denmark, Iceland, and South Korea—are outliers, as shown in Fig. 2 in the plot of leverage against the residual squared. We dropped these countries and estimate the results without them.

Fig. 3 is a scatter diagram omitting the three outlier countries, showing a positive slope that becomes flatter compared to Fig. 1.

Table 4
Average Correlation Coefficients and Pesaran (2007) Cross-Sectional Dependence (CD) Test.

Variable	CD test	*p*-value	Corr.	abs(corr)
Gini (SWIID)	11.58	0.000***	0.131	0.378
Gini (UTIP)	10.24	0.000***	0.238	0.372
Innovation (total patent applications/labor force)	4.98	0.000***	0.056	0.453
Innovation (total patents granted/labor force)	2.47	0.014**	0.032	0.350
Inflation	46.56	0.000***	0.527	0.529
Human capital	86.78	0.000***	0.983	0.983
Real GDP per capita	82.98	0.000***	0.940	0.940
Globalization	3.48	0.001***	0.039	0.462
Institutions	20.82	0.000***	0.236	0.368
Private sector credit	36.88	0.000***	0.418	0.728

Notes: Under the null hypothesis of cross-sectional independence CD ~ N(0,1). *** and ** indicate significance at the 1% and 5% levels, respectively.

Table 5
Pesaran's (2003) Panel Unit-Root Test in Presence of Cross-Sectional Dependence.

	Level		First difference
Variable	Constant	Constant with trend	Constant
Gini–SWIID	–0.364	–1.625	–4.267***
Gini–UTIP	–0.298	–1.534	–4.214***
Innovation–total patent applications/labor force	0.687	–1.640	–2.516***
Innovation–total patents granted/labor force	0.194	1.111	–4.794***
Inflation	–3.489***	–3.209***	–5.759***
Human capital (life expectancy)	0.691	2.882	–2.449***
Real GDP per capita	0.319	1.176	–2.151**
Globalization	0.257	–1.483	–2.159**
Institutions	–3.258***	–0.179	–3.521***
Private sector credit	2.131	2.507	–2.117**

Note: ***, **, and * denote significance at the 1%, 5%, and 10 % levels, respectively.

Table 6
Results of Common Correlated Effects Mean Group (CCEMG), Dependent variable: Income Inequality (Gini = SWIID), Innovation: Patents Application/Labor Force.

Variables	Model (1)	Model (2)	Model (3)	Model (4)
$Innovation_{it}$	0.0512*	0.0534*	0.0542*	0.0572*
	(0.0263)	(0.0276)	(0.0285)	(0.0299)
$Inflation_{it}$	0.0973***	–0.0907***	–0.0929***	–0.0872***
	(0.0277)	(0.0276)	(0.0276)	(0.0275)
$Real\ GDPPC_{it}$	–0.0224	–0.0200	–0.0397	–0.0360
	(0.0295)	(0.0294)	(0.0302)	(0.0301)
$Institutions_{it}$	–0.1980***	–0.1920***	–0.1901***	–0.1852***
	(0.0430)	(0.0429)	(0.0429)	(0.0428)
$Human\ Capital_{it}$	–0.8241***	–0.8412***	–0.9272***	–0.9350***
	(0.2041)	(0.2032)	(0.2071)	(0.2062)
$Globalization_{it}$		0.0805***		0.0745**
		(0.0306)		(0.0306)
$Private\ Sector\ Credit_{it}$			–0.0339**	–0.0311**
			(0.0135)	(0.0135)
Constant	–1.2021	–0.8801	–1.6482	–1.3142
	(0.7150)	(0.7211)	(0.7331)	(0.7421)
T	552	552	552	552
Number of Countries	23	23	23	23

Notes: All coefficients represent averages across groups. Coefficient averages computed as unweighted means. Standard errors in parentheses. *** and ** denote significance at the 1% and 5% levels, respectively.

Fig. 4 is a scatter diagram between the income inequality measure with the UTIP Theil's *T* statistic and total patent applications as innovation. The linear regression shows a higher positive slope than with other income inequality measures. Fig. 5 depicts the income inequality measure with EHII and total patent applications. The scatterplot indicates a positive relationship between these two variables, with a flatter slope.

5. Empirical results and discussion

To determine whether the explanatory variables have multicollinearity, we perform the variance inflation factor (VIF) test of Eq. (1) with all the control variables. Income inequality is measured with the SWIID, and two innovation indicators are used: the total number of patents over the total number of workers and total patent applications over the total number of workers. As shown in Table 3, the result demonstrates that the mean of the VIF is less than 5 for both models, which implies that no multicollinearity problem exists, as claimed by one of the advantages of using panel-data analysis. In terms of the endogeneity issue, Appendix Table A1 reveals that the Durbin-Wu-Hausman tests failed to reject the null hypothesis, in which the *p*-value of the tests is greater than 0.05. The results are similar for both lagged innovation and R&D expenditure, which are used as instruments. This finding concludes that *INNO* is exogenous because the residuals ε_{it} and v_{it} are uncorrelated in Eq.s (2a) and (2b), and no potential endogeneity is found due to reverse causality from income inequality to innovation.

Table 7
Results of Common Correlated Effects Mean Group (CCEMG) with Interaction Term, Dependent variable: Income Inequality (Gini - SWIID), Innovation = Patent Application/Labor Force.

Variables	Model 1(a)	Model 1(b)
Innovation$_{it}$	0.2290***	0.2191***
	(0.0855)	(0.0360)
Inflation$_{it}$	0.0857***	0.1232***
	(0.0275)	(0.0270)
Real GDP per Capita$_{it}$	–0.0213	–0.0064
	(0.0292)	(0.0296)
Institutions$_{it}$	–0.1911***	–0.1482***
	(0.0426)	(0.0420)
Human Capital$_{it}$	–0.8252***	–1.0191***
	(0.2021)	(0.2002)
Globalization	–0.2862***	
	(0.0810)	
Globalization$_{it}$ *x Innovation*$_{it}$	0.0547***	
	(0.0199)	
Private Sector Credit$_{it}$		–0.2362***
		(0.0347)
Private Sector Credit$_{it}$ *x Innovation*$_{it}$		0.0483***
		(0.0077)
Constant	0.0589	–0.6112
	(0.794)	(0.7260)
Observations	552	552
Number of Countries	23	23

Notes: All coefficients represent averages across groups. Coefficient averages computed as unweighted means. Standard errors in parentheses. *** and ** denote significance at the 1% and 5% levels, respectively.

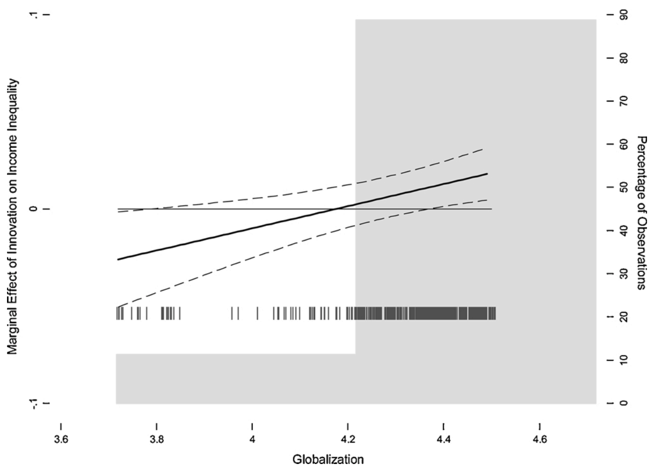

Fig. 6. The Marginal Effect of Globalization on Innovation–Income Inequality Nexus.

Before conducting further analysis, we evaluate the CD of the variables, whether the first or second generation of time-series panel estimations, using the Pesaran (2007) CD test. The empirical results reported in Table 4 indicate that all variables reject the null hypothesis of cross-sectional independence at the conventional level of significance. Therefore, this study uses the second-generation time-series panel analysis to analyze the relationship between innovation and income inequality.[8] Table 5 presents the Pesaran (2007) panel unit-root test with CD. The results indicate that all variables are stationary at the integration of order one or I(1), except inflation with a constant and a constant with trend, whereas institutions with a constant are stationary at level or I(0).

Table 6 reports the empirical results of the role of innovation in income inequality, in which the income inequality is measured with the SWIID, and innovation is measured by the total patent applications over the total number of workers. Model (1) is the baseline model, in which only four control variables are included: *RGDPPC*, human capital, inflation, and institutions. The empirical results indicate that innovation is a positive and statistically significant determinant of income inequality at the 10 percent level throughout

[8] The Pesaran (2006) cross-sectional dependence test was also performed on the residual of the CCEMG estimations, and all the residuals from various models also reject the null hypothesis of cross-sectional independence.

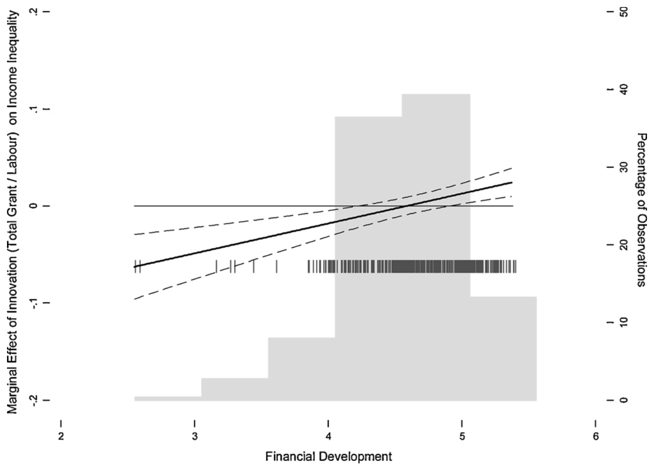

Fig. 7. The Marginal Effect of Financial Development on Innovation–Income Inequality Nexu.

Table 8
Results of Common Correlated Effects Mean Group (CCEMG) using Total Patent Applications/Labor Force, Dependent variable: Income Inequality (Gini - SWIID), Innovation: Patent Application / Labor Force.

Variables	Model (4a) Without Interaction	Model (5a)	Model (6a)	Model (7a)	Model (8a) With Interaction	Model (9a)
Innovation$_{it}$	0.0037	0.00358	0.00356	0.00343	0.0290 (0.0897)	–0.146***
	(0.0046)	(0.00459)	(0.00459)	(0.00457)		(0.0358)
Inflation$_{it}$	0.0985***	0.0921***	0.0944***	0.0888***	0.0927***	0.102***
	(0.0276)	(0.0276)	(0.0275)	(0.0275)	(0.0277)	(0.0272)
Real GDP per capita$_{it}$	–0.0204	0.0177 (0.0292)	0.0370 (0.0300)	0.0331 (0.0299)	0.0171 (0.0293)	0.0103 (0.0302)
	(0.0294)					
Institutions$_{it}$	–0.1940***	0.188***	0.186***	0.181***	0.188***	0.171***
	(0.0432)	(0.0430)	(0.0431)	(0.0430)	(0.0431)	(0.0426)
Human capital$_{it}$	–0.8450***	0.862***	0.946***	0.953***	0.865***	0.978***
	(0.2050)	(0.204)	(0.208)	(0.207)	(0.204)	(0.205)
Globalization$_{it}$		0.0795***		0.0736**	–0.0585	
		(0.0306)		(0.0306)	(0.0800)	
Private sector credit$_{it}$			–0.0333**	0.0306**		–0.137***
			(0.0135)	(0.0135)		(0.0280)
Innovation (patent) x Globalization$_{it}$					0.0594***	
					(0.0209)	
Innovation (patent) x private sector credit$_{it}$						0.0322***
						(0.00765)
Constant	–1.250*	–0.926	1.924***	–1.346*	–1.025	–1.008
	(0.722)	(0.729)	(0.282)	(0.749)	(0.807)	(0.745)
Observations	552	552	552	552	552	552
Number of Countries	23	23	23	23	23	23

Notes: All coefficients represent averages across groups. Coefficient averages computed as unweighted means. Standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10 % levels, respectively.

the four models. Human capital, which is proxied by life expectancy, and institutions have a negative relationship and are statistically significant determinants of income inequality, whereas inflation has a positive and significant relationship with income inequality. This implies that greater human capital and better institutions narrow the income inequality gap, whereas higher inflation widens income inequality. The *RGDPPC* is insignificant in influencing income inequality.

Model (2) includes the globalization variable, and our finding suggests that inflation, human capital, and institutions are statistically significant, and globalization tends to increase income inequality because the coefficient is positive. As in Model (3), which includes private sector credit (financial development), the three control variables have a negative relationship, except inflation and financial development. This result reveals that financial development widens income inequality, and this finding is in line with Banerjee and Newman (1993) and Tan and Law (2012). Model (4) includes all the variables in the specification, and the results reveal that innovation has a weak but significant effect on income inequality, *RGDPPC* is insignificant, and other variables remain significant determinants of income inequality at the conventional level. Based on Models (1)–(4), the findings demonstrate that innovation is weak but significant in ameliorating the income–inequality gap in developed countries. Better institutions and human capital are important determinants in reducing income inequality in these economies, but greater globalization and financial development tend to

Table 9
Results of Common Correlated Effects Mean Group (CCEMG) using Total Patent Applications/Labor Force, Dependent variable: Income Inequality (Gini–UTIP), Innovation: Patents Granted/Labor Force.

Variables	Model (10a) Without Interaction	Model (10b)	Model (10c)	Model (10d)	Model (10e) With Interaction	Model (10f)
Innovation$_{it}$	0.0012*	0.0012*	0.0013**	0.0013**	−0.0165	−0.0181***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0110)	(0.0043)
Inflation$_{it}$	0.0114***	0.0115***	0.0108***	0.0108***	0.0113***	0.0118***
	(0.0034)	(0.0034)	(0.0033)	(0.0033)	(0.0034)	(0.0033)
Real GDP per capita$_{it}$	–0.0006	–0.0005	0.0024	–0.0030	–0.0004	–0.0010
	(0.0036)	(0.0036)	(0.0036)	(0.0037)	(0.0036)	(0.0036)
Institutions$_{it}$	–0.0157**	–0.0156**	–0.0086*	–0.0172**	–0.0116**	–0.0105**
	(0.0078)	(0.0069)	(0.0052)	(0.0074)	(0.0051)	(0.0051)
Human capital$_{it}$	–0.0943***	–0.0940***	–0.0940***	–0.1150***	0.0985***	0.1250***
	(0.0249)	(0.0249)	0.1210***	(0.0250)	(0.0250)	(0.0246)
Globalization$_{it}$		0.0162***		0.0129***	–0.0129	
		(0.0038)		(0.0037)	(0.0098)	
Private sector credit$_{it}$			0.0066***	0.0061***		–0.0201***
			(0.0016)	(0.0016)		(0.0034)
Innovation (total patents granted) x globalization$_{it}$					0.0147***	
					(0.0026)	
Innovation (patents granted) x private sector credit$_{it}$						0.0042***
						(0.0009)
Constant	–0.367***	–0.373***	–0.373***	–0.469***	–0.3280***	–0.3870***
	(0.0873)	(0.0887)	(0.0887)	(0.0902)	(0.0987)	(0.0897)
Observations	575	575	575	575	575	575
Number of Countries	23	23	23	23	23	23

Notes: All coefficients represent averages across groups. Coefficient averages computed as unweighted means. Standard errors in parentheses. ***, **, and * denote significance at 1%, 5%, and 10 % levels, respectively.

Table 10
Results of Common Correlated Effects Mean Group (CCEMG) using Total Patents Granted/Labor Force, Dependent variable: Income Inequality (Gini - EHII), Innovation: Patents Granted/Labor Force.

Variables	Model (11a) Without Interaction	Model (11b)	Model (11c)	Model (11d)	Model (11e) With Interaction	Model (11f)
Innovation$_{it}$ (Patents Granted/ Labor)	0.0118**	0.0120***	0.0107***	0.0111***	−0.0844**	−0.103***
	(0.0051)	(0.0039)	(0.0037)	(0.0037)	(0.0362)	(0.0325)
Inflation$_{it}$	0.0863***	–0.0829***	–0.0768***	–0.0749***	–0.0822***	–0.0727***
	(0.0193)	(0.0193)	(0.0191)	(0.0192)	(0.0194)	(0.0189)
Real GDP per capita$_{it}$	–0.1620	–0.1632	–0.1351***	–0.1372***	–0.1602***	–0.1482***
	(0.1026)	(0.1026)	(0.0272)	(0.0272)	(0.0270)	(0.0271)
Institutions$_{it}$	–0.0745**	0.0717**	0.0722**	0.0705**	0.0707**	0.0701**
	(0.0310)	(0.0310)	(0.0306)	(0.0306)	(0.0311)	(0.0301)
Human capital$_{it}$	–2.6530***	2.6571***	2.684***	2.6861***	2.6294***	2.7032***
	(0.2190)	(0.2182)	(0.2154)	(0.2152)	(0.2230)	(0.2123)
Globalization$_{it}$		0.0404**		0.0366**	–0.0780	
		(0.0183)		(0.0150)	(0.0666)	
Private sector credit$_{it}$			–0.0443***	–0.0423***		–0.1282***
			(0.0121)	(0.0123)		(0.0265)
Innovation x globalization$_{it}$					0.0409**(0.0178)	
Innovation x private sector credit$_{it}$						0.0248***
						(0.0071)
Constant	–6.572***	–6.400***	–6.784***	–6.661***	–6.143***	–6.339***
	(0.755)	(0.761)	(0.745)	(0.754)	(0.870)	(0.746)
Observations	424	424	424	424	424	424
Number of countries	23	23	23	23	23	23

increase income inequality.

This study further investigates the indirect channels or mechanisms in the role of innovation in income inequality by interacting two variables: globalization and financial development. The empirical results are reported in Table 7, focusing on the interaction term and the marginal effect. According to Brambor et al. (2006), individual variables, such as innovation, and interaction between two individual variables (globalization and financial development) should not be the main concern. To evaluate the significance of the interaction term, the new standard error is calculated using Eq.s (8)–(9). Model (1a) shows that the interaction term between

Table 11
Robustness Checks using the Augmented Mean Group (AMG) Estimator, Dependent variable: Income Inequality (Gini - SWIID), Innovation: Patent Applications/Labor Force.

Variables	Model (12a) Without Interaction	Model (12b)	Model (12c)	Model (12d)	Model (12e) With Interaction	Model (12f)
Patents/Labor$_{it}$	0.00326	0.00352	0.00304	0.00349	–0.229	–0.243***
	(0.00528)	(0.0210)	(0.0230)	(0.0210)	(0.198)	(0.0683)
Inflation$_{it}$	0.106***	–0.100***	–0.108***	–0.101***	–0.0951***	–0.137***
	(0.0282)	(0.0372)	(0.0364)	(0.0362)	(0.0316)	(0.0470)
Real GDP per capita$_{it}$	–0.0284	–0.0361	–0.0414	–0.0416	–0.0337	–0.0547
	(0.0272)	(0.0700)	(0.0598)	(0.0636)	(0.0695)	(0.0675)
Institutions$_{it}$	–0.179***	0.171***	0.166**	0.162**	0.170**	0.127**
	(0.0437)	(0.0656)	(0.0653)	(0.0637)	(0.0665)	(0.0619)
Human capital$_{it}$	–1.099***	–1.145**	–1.269***	–1.264***	–1.122**	–1.256***
	(0.196)	(0.452)	(0.487)	(0.485)	(0.436)	(0.444)
Globalization$_{it}$		0.0852**		0.0842**	0.0291**	
		(0.0404)		(0.0382)	(0.0147)	
Private sector credit$_{it}$			–0.0468**(0.0223)	–0.0453**(0.0212)		–0.242***(0.0723)
Patents x globalization$_{it}$					0.0544**(0.0268)	
Patents x private sector credit$_{it}$						0.0532***(0.0150)
Constant	–1.788**	–1.510	–2.263	–1.873	–0.557	–0.891
	(0.710)	(1.795)	(1.816)	(1.883)	(1.488)	(1.364)
Observations	552	552	552	552	552	552
Number of countries	23	23	23	23	23	23

Notes: Standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10 % levels, respectively.

innovation and globalization is positive and statistically significant, which implies that innovation and globalization both widen income inequality. This finding is consistent with Anderson (2009); Krugman (2008), and Stiglitz (2012), who find that innovation and globalization cause income inequality. Model (1b) also reveals that the interaction between innovation and financial development is positive and statistically significant, and both variables widen the income–inequality gap because the coefficient of the interaction term is negative.

In terms of the marginal effect, Fig. 6 plots the marginal effect of innovation on income inequality along the 95 percent confidence bands over the minimum and maximum values of globalization (Kingsley et al., 2017). The figure also plots the frequency distribution of globalization, in which the bar of the histogram represents the number of observations of globalization in that range of values. As shown in this figure, innovation has a statistically significant positive effect on income inequality over most of the values of globalization in the sample countries (from 4.4 to 4.5). For example, when globalization is 4.4, the marginal effect of innovation on income inequality is approximately 0.01 percentage points. Critically, because the confidence interval bands do not cross zero for values of globalization smaller than 4.4, we can conclude that the marginal effects are statistically different from zero (at the 95 percent level) over the range of globalization from 4.4 to 4.5. A closer look at the histogram reveals that approximately 90 percent of the observations in the sample have values of globalization of more than 4.4.

As depicted in Fig. 7, innovation has a statistically significant positive effect on income inequality over most of the values of financial development in the sample countries (smaller than 4.1 and larger than 5.1). For instance, when financial development is 3, the marginal effect of innovation on income inequality is approximately –0.5 percentage point. Importantly, because the confidence interval bands do not cross zero for values of financial development smaller than 4.1 and larger than 5.1, we confirm that the marginal effects are statistically different from zero (at the 95 percent level) over the range of financial development smaller than 4.1 and larger than 5.1. A closer look at the histogram indicates that approximately 62 percent of the observations in the sample have values of financial development smaller than 4.1 and larger than 5.1.

Table 8 presents an alternative innovation variable, total patent applications over the total number of workers, and income inequality is still measured using the SWIID. Models (4a)–(7a) do not include interaction terms whereas Models (8a)–(9a) include them. In the models with interaction terms, innovation, represented by total patent applications, is an insignificant determinant of income inequality. Inflation has a positive impact on innovation, which indicates that higher inflation widens income inequality. The results for the variables for institutions and human capital show that better institutions and higher human capital reduce income inequality. *RGDPPC* is insignificant in all the models. Globalization increases income inequality, as shown in Model (5a), where the coefficient of this variable is positive. Private sector credit is also significant, even in Model (6a), where total patent applications is used to measure innovation. Model (7a) indicates that when all variables are included in the specification, both globalization and financial development retain a positive sign and are significant determinants of income inequality. The marginal effects of Models (8a)–(9a) indicate similar patterns in the total number of patents as shown in Figs. 6 and 7. This demonstrates that the effect of innovation on income inequality is positive, and the channels of globalization and financial development failed to narrow income inequality.[9]

Table 9 present the empirical results of the same variable but using a different measure of income inequality, the UTIP. The results indicate that innovation is a positive and significant determinant of income inequality at the conventional level in Models (6b) and (7b)

[9] To conserve space, the results for the marginal effect of total patents granted as innovation are not reported but are available upon request.

but weakly significant in Models (4b) and (5b). This finding suggests that innovation failed to reduce income inequality. Institutions and human capital are significant in all the models in reducing income inequality, but inflation worsens income inequality. Overall, the results are similar to those in Table 8, and the marginal effect results in a similarly positive pattern in Figs. 6 and 7.

6. Robustness checks

This study also performs robustness checks using the EHII income inequality measure and total patent applications as a measure of innovation. The empirical results reported in Table 10 reveal that innovation has a positively significant effect on income inequality in Models (10a)–(10d). This implies that a different measure of innovation, which measures the quality of innovation, also yields a positive and significant effect on income inequality. The interaction Models (10e) and (10f) indicate that both globalization and financial development have a positive mediating impact on income inequality. The findings are quantitatively similar to those reported in Tables 6 and 8.

We also provide a second set of robustness checks using the augmented mean group (AMG) estimator developed by Eberhardt (2012) and Eberhardt and Bond (2009).[10] The AMG method includes year dummies in the model and can deal with CD and slope heterogeneity. The unobservable common factors in the AMG method are treated as a common dynamic process, but the CCEMG method includes unobservable common factors in the error term. Like the CCEMG estimator, the AMG estimator is robust to parameter heterogeneity and CD. The main difference between the CCEMG and AMG estimators is the approximation method of the unobserved common factors (f_t) in Eq. (2). The AMG estimator uses a two-step method to estimate the unobserved common dynamic effect and allows for CD by including the common dynamic effect parameter. Table 11 reports the results of AMG, and the findings are quantitatively similar to those obtained using the CCEMG estimator, as shown in Tables 6–8. All coefficients have the same sign as those obtained with the CCEMG estimator; innovation is a significant determinant of income inequality. Inflation still increases income inequality, but better institutions and human capital reduce the income–inequality gap. Globalization and financial development have positive roles in mediating the widening of income inequality in developed countries. Overall, the empirical results are robust to the alternative measurement of innovation, income inequality, and the estimation method, so our findings remain consistent.

7. Conclusions

The role of innovation in income inequality and the channels in their nexus have generated a strand of literature because innovation tends to promote economic growth. This study examines the potential determinants of income inequality in twenty-three developed economies (after dropping three outlier countries) over the period 1990–2015, using time-series panel-data techniques. This study focuses on developed countries because these economies have more innovation than developing countries, and over the past two decades income inequality did not change much in developing countries. In the theoretical literature, in addition to innovation, the determinants of income inequality are economic development, inflation, institutions, human capital, globalization, and financial development. Nevertheless, some economists argue that globalization and financial development widen income inequality, and this study revisits the role of these two variables. The econometric methodology adopted in this study takes into account the important characteristics of the hypothesis: dynamics, heterogeneity, and CD.

The empirical results indicate that innovation is significant in widening income inequality, especially the number of patents granted. The findings demonstrate that institutions and human capital are negatively associated with or reducing income inequality in developed economies. However, higher inflation, globalization, and financial development tend to increase or worsen income inequality. The robustness checks using the AMG also show that our empirical results are robust to an alternative estimation method. This study also examines whether globalization and financial development can act as mediators in influencing the innovation–income inequality nexus. The findings demonstrate that globalization and financial development act as mediators to worsen income inequality. The marginal effect of innovation has a positive relationship with income inequality through globalization and financial development.

In terms of implications, monitoring and reducing income inequality are vital for sustainable economic growth in a country. Its wealth should not be concentrated in the hands of capitalists, and everyone should have equal economic opportunity. To reduce income inequality, the national wealth needs to be shared, and all talents need opportunities for innovation. Innovation should be encouraged in an economy because all technological advancements have the potential to promote productivity and economic growth in the long run. In addition, better-quality human capital and better institutional quality are needed to address income inequality. However, monitoring openness as well as maintaining price stability and access to finance are also crucial in reducing income inequality. Our findings use the number of patent applications and patents granted, given the global innovative index in the digital age, and it is vital to explore whether the innovative index also show similar findings. Other potential confounders, such as changes in the structure of industry and international trade, also have the potential to influence income inequality. We leave the exploration of these possibilities to future research.

[10] Using Monte Carlo simulations, Eberhardt and Bond (2009) point out that the AMG and CCEMG performed similarly well in terms of bias or root mean squared error in panels with nonstationary variables and multifactor error terms (cross-sectional dependence).

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Appendix A

Table A1
Results of the Endogeneity Test.

Variables	Model (1a)	Model (2a)	Model (3a)	Model (4a)	Model (5a)	Model (6a)
	Dependent variable: Gini (SWIID)			Dependent variable: Gini (SWIID)		
	Instrument: Lagged Innovation$_{t-1}$			Instrument: R&D Expenditure/GDP		
Innovation$_{it}$	0.0294***	0.0162***	0.0355***	0.455**	0.316***	0.501**
	(0.00514)	(0.00455)	(0.00513)	(0.201)	(0.113)	(0.243)
Real GDPPC$_{it}$	–0.148***	–0.162***	–0.119***	–0.119	–0.122*	–0.0598
	(0.0189)	(0.0140)	(0.0156)	(0.0949)	(0.0649)	(0.112)
Inflation$_{it}$	–0.541***	–0.314**	–0.740***	–4.199*	–1.440	–4.674
	(0.164)	(0.138)	(0.154)	(2.497)	(1.392)	(2.898)
Institutions$_{it}$	–0.483***	–0.497***	–0.618***	0.881	0.189	0.815
	(0.0699)	(0.0518)	(0.0584)	(0.660)	(0.356)	(0.681)
Human Capital$_{it}$	1.171***	1.224***	1.168***	6.665**	5.877***	6.826**
	(0.284)	(0.328)	(0.256)	(2.791)	(1.302)	(3.082)
Private Sector Credit$_{it}$		0.181***			0.431***	
		(0.0127)			(0.0924)	
Globalization$_{it}$			–0.188***			–0.596***
			(0.0367)			(0.196)
Constant	1.537	6.069***	7.635***	25.78*	0.481	29.25*
	(1.281)	(0.178)	(0.262)	(13.38)	(6.183)	(16.15)
Durbin (score) χ^2	1.518 (0.217)	2.265 (0.132)	3.063 (0.080)	0.025 (0.873)	2.397 (0.122)	0.671 (0.413)
Wu-Hausman F test	1.502 (0.221)	2.245 (0.135)	3.040 (0.082)	0.025 (0.874)	2.364 (0.125)	0.659 (0.417)
Observations	529	529	529	414	414	414

Notes: Standard errors in parentheses. *** and ** denote significance at the 1% and 5% levels, respectively.

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Appendix B. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.ecosys.2020.100815.

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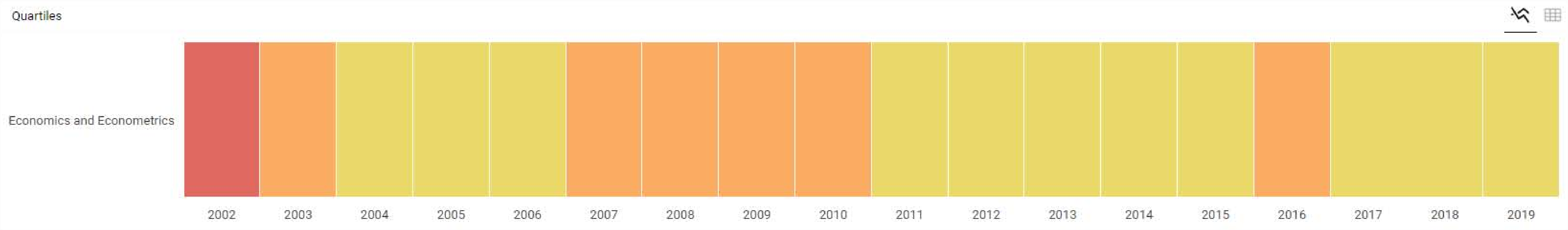
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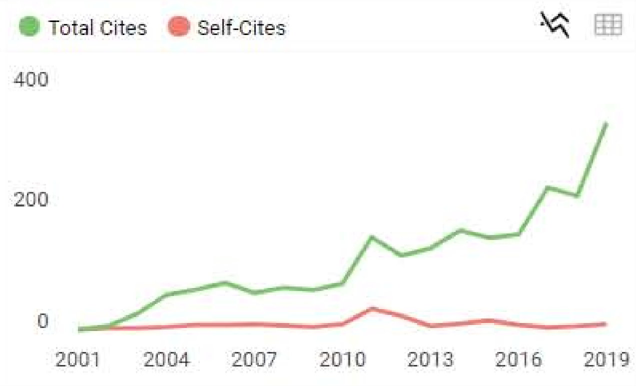

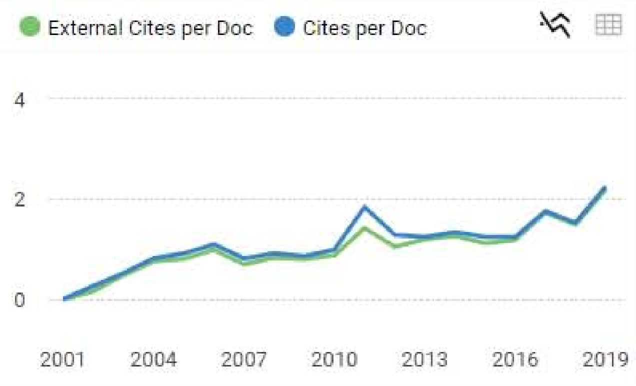

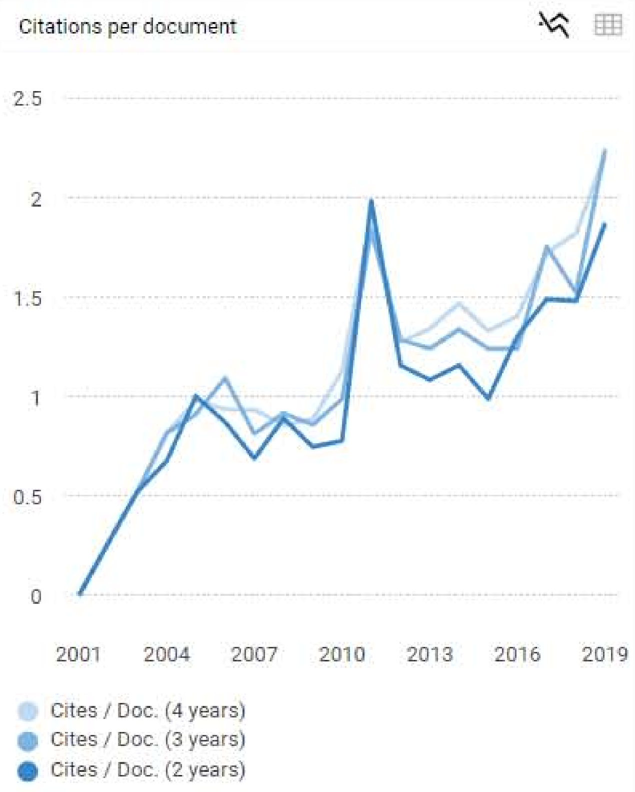

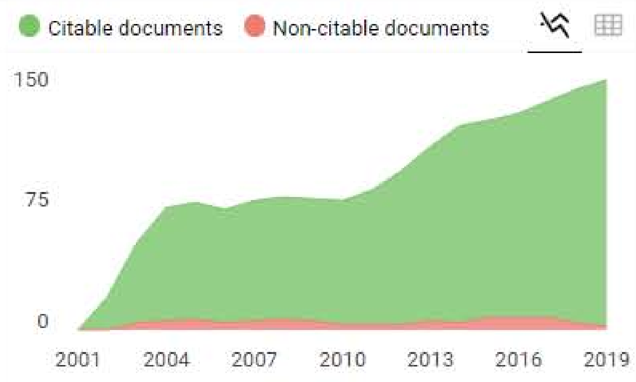

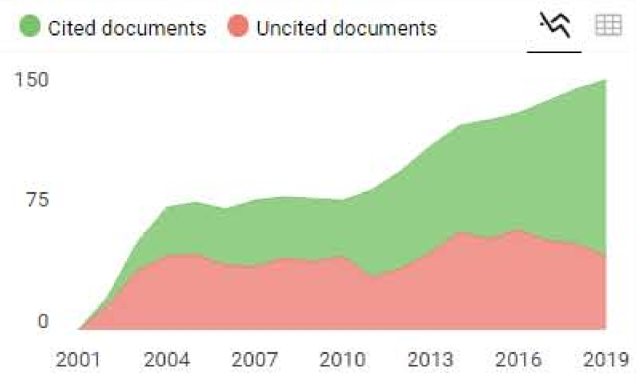

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