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THE NONLINEAR RELATIONSHIP BETWEEN TECHNOLOGICAL DEVELOPMENT AND INCOME INEQUALITY: EVIDENCE FROM DYNAMIC PANEL MODEL WITH THRESHOLD EFFECT

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This study revisits the innovation-inequality nexus and tests the technological Kuznets curve hypothesis suggesting that technology can induce or reduce inequalities depending on the level of technological development. Applying a recently developed dynamic panel model with endogeneity and threshold effects to a panel of 72 countries, I find a significant U-shaped curvilinear relationship between innovation and income inequality which is robust to different measures of innovations and a different estimation technique. Furthermore, it was shown that achieving a certain level of technological development can change how economic growth and financial development affect income inequality.

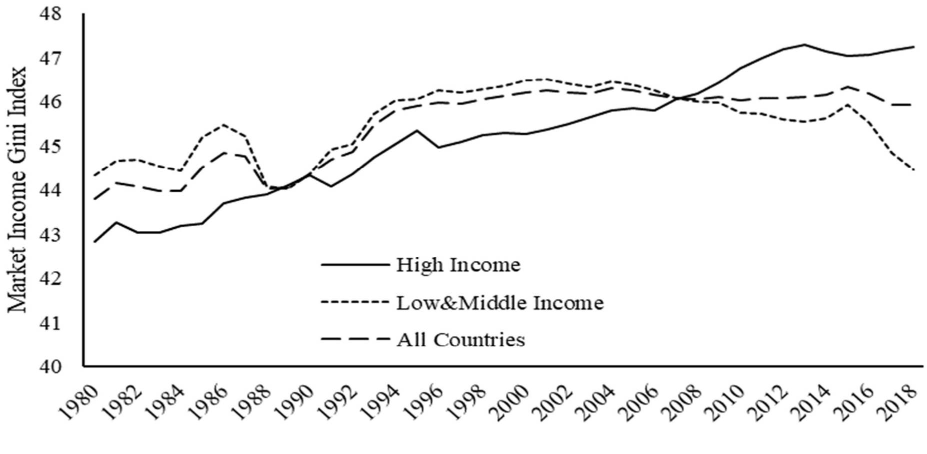
Keywords: Nonlinearity; Dynamic Panel, Threshold Effects, Income Inequality, Innovation
JEL Classification: D3, O33, N30

1. INTRODUCTION

Innovation is crucial for improving productivity and boosting economic growth, but it is also known to be one of the factors that disrupts income distribution. Although there are a lot of publications on innovation-inequality nexus, the existing literature is inconclusive as it provides conflicting findings. Prevailing view is that technological development induces income inequality as it follows from the skill-biased technological change theory (Aghion et al., 2019; Law et al., 2020; Antonelli and Tubiana, 2020). At the same time, some of the recent publications also provide evidence of the negative relationship between technological change and inequality (Benos and Tsiachtsiras, 2019; Canh et al., 2020). Based on conflicting findings in the literature, my study suggests that there is a nonlinearity in the innovation-inequality relationship. It must be a case that in some countries the effect of innovation on inequality is positive while in other countries it is negative or not significant.

This idea can be translated into the technological Kuznets curve (TKC) hypothesis, which posits that there is a U-shaped or inverted U-shaped relationship between level of income inequality and level of technological development. Therefore, there should be a certain level of technological development after which the relationship is reversed. Because technological change takes relatively long time to manifest itself in improved productivity and economic growth, both versions of TKC should be considered as a cross-sectional pattern that suggests, at least partially, a causal link between innovation and inequality.

Relying on the comparative analysis of within-country income inequality across different countries, the first version of TKC hypothesis (U-shaped relationship) seems more likely to be the case. According to statistical data for the last three decades, decline in the global income inequality has been driven mostly by developing countries while developed countries have been exhibiting an increase in inequality of market income. In more details, this trend is shown by Furceri and Ostry (2019) who analyze determinants and trends of market income inequality across 108 countries. Using the IMF classification of countries by level of development, authors provide evidence of the striking difference in the trend of income inequality between advanced and other groups of countries. In particular, developing countries have been demonstrating declining levels of inequality since the mid-90s, while inequality in advanced countries has been steadily on the rise from the end of the 80s.

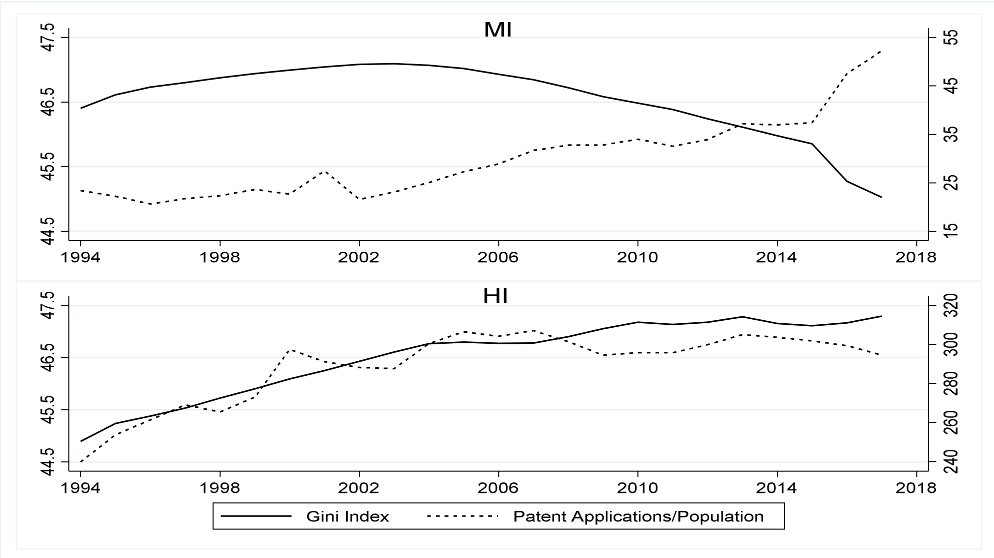


Note: Data for market income Gini index was extracted from Standardized World Income Inequality Database (SWIID), 2020.; Countries were classified according to the World Bank income categories. Dynamic nature of the classification was taken into account.

Figure 1. Market Income Inequality Across Income Groups, 1980-2018

The divergence in terms of income inequality can also be found between high-income and non-high-income countries. According to the results reported in Figure

1, in the early 90s both high-income and non-high-income countries were experiencing steady increase in income inequality. However, by the late 90s levels of income inequality in low- and middle-income countries stabilized and started declining while inequality in high-income countries continued to rise exceeding global level of income inequality after the financial crisis in 2007-2008. By 2018 the average level of inequality measured by Gini index for market income achieved 0.472 in high-income countries, 6.2 % higher than in low- and middle-income countries (Fig.1).



Note: Gini index for market income was retrieved from SWIID (2020), patent applications data was retrieved from WIPO data base for PCT patent applications by resident, then it was divided by total population retrieved from the Penn World Table (version 10). Countries were classified according to the World Bank income categories. Dynamic nature of the classification was taken into account.

Figure 2. Relationship between Gini Index (Left Y-Axis) and Innovation Proxied by Patent Applications Weighted by Population (Right Y-Axis) in High- (HI) and Middle-Income (MI) Countries

Trend of increasing inequality in developed countries is at odds with the traditional view of the relationship between economic development and inequality proposed by Kuznets Curve (Kuznets, 1955). According to the Kuznets Curve (KC) hypothesis, the relationship between growth of income and income inequality can be described by the inverted U-shaped curve. In this framework, developed countries are predicted to have a decline in income inequality. According to Kuznets, technology is one of the forces that counteracts the concentration of savings and increases dynamism of the economy which should lead to lower income inequality. However, empirical data shows the opposite trend. Galbraith and Conceição (2000) find similar pattern when testing the KC hypothesis for OECD countries in 1970-1990. They suggest the augmented KC in which high-income countries, usually technological leaders, move from a downward slope of the KC to a new upward slope. Weil (2005) also noticed the mismatch between empirical data and theoretical conjectures and suggests that after inverted U-shaped cycle is complete, advanced countries face increasing income inequality caused by technological change, increase in international trade and superstar firm dynamics.

Further look at the relationship between innovation and inequality of income shows that innovation activity measured by patent applications is intensifying in both middle- and high-income countries (Fig.2). At the same time, dynamics of income inequality measured by Gini index is different. In 1994-2017, patent applications in high-income countries are much higher than in middle-income countries and negatively associated with income inequality, while middle-income countries have negative correlation between both variables. Either innovation plays no role in this dynamics or innovation contributes differently depending on the level of innovation. According to the existing literature, the former argument is not the case. For example, Van Reenen (2011) finds that technology plays a significant role in the trend of increasing income inequality in OECD countries, and Jaumotte et al. (2013) report that technology exerts higher impact on inequality than globalization. It should be noted that other factors can also affect inequality in non-linear manner (Gravina and Lanzafame, 2021). For comparison, the existing literature on inequality of income found nonlinear effect of economic development (Kuznets, 1955), financial development (Nikoloski, 2013), trade openness (Jalil, 2012), human capital and institutions on income inequality (Canh et al., 2020), but the TKC was not given the same attention. Not taking into account nonlinear relationship between innovation and inequality can be one of the reasons behind conflicting results in empirical literature.

Previous literature on the TKC is scarce and captures potential nonlinear effects of innovation with the help of quadratic regression models (Gravina and Lanzafame, 2021; Leoncini, 2017; Kim, 2012). However, this approach has several limitations. Firstly, quadratic terms cannot capture threshold effects, i.e., changes in relationship between income inequality and other determinants of inequality when level of technological development reaches a certain threshold. Secondly, quadratic regression models suffer from the multicollinearity problem (Narayan and Narayan, 2010). In order to overcome this drawback, this paper adopts a dynamic panel model with threshold and endogeneity. This is a novel method developed by Seo and Shin (2016) that deals with unobserved heterogeneity and threshold effects in panel data. Moreover, dynamic panel framework and GMM estimation used in the model allow to address endogeneity of regressors and persistence of a dependent variable, which in our case is income inequality. To the best of my knowledge, this study is a first attempt to apply dynamic panel threshold model with endogeneity to analyze the innovation-inequality nexus. Furthermore, I take into account that innovation is a hard-to-measure variable. Some innovations are incremental and may not affect income distribution, while radical innovations may significantly disrupt distribution of income through creative destruction. Relying on previous research, I focus on output measures of innovations that have a comprehensive data set. Three indicators of innovation are used: investment specific technological change proxied by relative price of investment goods, weighted by population count of patent application and patent grants.

Applying dynamic threshold model to a panel data for 72 high- and middle-income countries over 1994-2017, I investigate whether threshold effects in innovation inequality relationship can reconcile conflicting results found in empirical literature. Findings of this paper support the U-shaped version of the TKC hypothesis: increase in innovation activity reduces inequality until reaching a certain threshold after which it starts exerting the opposite effects. To test nonlinearity, I perform a bootstrap linearity test proposed by Seo et al. (2019) and U-test developed by Lind and Mehlum (2010). Robustness check is conducted by including additional control variables and using different specification and estimation technique – two-step System GMM (Arellano and Bover, 1995; Blundell and Bond, 1998). The findings also help to explain the divergence in the trends of income inequality observed between high-income and non-high-income countries.

The rest of the paper is organized as follows: Section 2 briefly reviews relevant literature; Section 3 lays out the estimation strategy; Section 4 describes the data; Section 5 provides the estimation results; Section 6 checks robustness of the results; Section 7 summarizes and concludes the paper.

2. REVIEW OF RELATED LITERATURE

Most of the recent literature on the innovation-inequality nexus is empirical studies that provide evidence for either positive or negative impact of innovations on income inequality. Positive effect is found by Permana et al. (2018), Aghion et al. (2019), Law et al. (2020), Antonelli and Tubiana (2020) and others. Law et al. (2020) use observations from 23 developed countries and the Common Correlated Effect Mean Group (CCEMG) method to confirm positive effect of innovations on inequality. Authors also investigate the innovation-inequality nexus in relation to the level of financial development and globalization and find that interaction between innovation and these two factors also widens income inequality. Antonelli and Tubiana (2020) apply a two-way fixed effect estimator to a panel data of 20 developed countries over 27 years when regressing within-country Gini index on investments in R&D and on the quota of knowledge intensive business services. Their results also provide evidence of positive impact of technological change on income inequality.

However, some studies find that innovations can improve income inequality. Canh et al. (2020) examine the impact of innovations through internet and mobile usage in a sample consisting of 87 countries over 13 years and come to a conclusion that innovations reduce income inequality. Benos and Tsiachtsiras (2019) also present empirical evidence of negative relationships between innovations and unequal distribution of personal income. Based on panel data analysis and instrumental variable estimation technique, Benos and Tsiachtsiras find that increase in innovations reduces top income inequality within countries. Antonelli and Gehringer (2017) apply quantile regression technique to 39 countries and reach a conclusion that income inequality is a consequence of slow technological change – the faster rate of technological change, the lower the income inequality via its negative effects on rent inequalities. Some other studies come to conflicting findings when using different measures of innovations. In particular, Wlodarczyk (2017) finds positive relationship between innovations and inequality when innovations are measured by R&D expenses, and negative when innovations are measured by patent applications over the similar time period for sample consisting of 30 European countries.

Despite the fact that conflicting empirical evidence suggests potential nonlinear effects, literature that investigates existence of nonlinear relationship between innovation and inequality are quite scarce. Nonlinear U-shaped relationship between innovation and inequality can be inferred from works of Conceição and Galbraith (2000) that posit the augmented Kuznets Curve hypothesis. Conceição and Galbraith (2000) show that in majority of countries the innovation-inequality relationship follows inverted U-shaped curve where introduction of new technologies widens inequality but through diffusion it leads to more equal income distribution afterwards. At the same time, in countries that achieved high level of technological development, innovations increase the divide between knowledge-intensive and traditional sectors leading to higher levels of inequality. Based on this observation, some studies (Kim, 2012; Gravina and Lanzafame, 2021) suggest what is known as the Technological Kuznets curve hypothesis.

There are two versions of TKC in the existing literature. TKC can either be U-shaped or inverted U-shaped curve. The idea behind inverted U-shape relationship is that at first, innovation disrupts income distribution making it more unequal. During this phase, Kuznets (1955) describes technological change as a force that leads to a rapid growth of younger industries coinciding with a declining share of older industries. Because only few new industries are main beneficiaries from a new technology, income inequality in a country will rise. But as innovation diffuses through economy, initial innovators' rents get diluted, and income inequality declines (Barro, 1999). Thus, this version of the TKC can be viewed as an extension of the original KC because innovation drives economic growth. That is why, as was noted by Barro (1999), TKC will follow inverted U-shaped curve only if innovation is manifested in increase of real GDP per capita.

U-shaped version of the TKC is based on the Schumpeter's view of a role of innovation in economic growth. From this perspective, technological development can be classified into two patterns of innovations: widening innovation pattern, known as Schumpeter Mark 1, and deepening innovation pattern, or Schumpeter Mark 2 (Malerba and Orsenigo, 1996). Widening innovation corresponds to Schumpeter's concept of "creative destruction" and characterized by a low concentration of innovative activities with numerous new innovating firms. It creates new opportunities for entrepreneurs and lowers entry barriers which are associated with equalizing effects of innovation. Deepening pattern is characterized by "creative accumulation" with a small number of large inventors continuously innovating based on the accumulated research base. At this stage of technological development, innovative activities become more concentrated and require higher R&D expenditures to innovate raising entry barriers (Malerba and Orsenigo, 1996). During this phase, innovation is expected to exacerbate existing income inequality.

Kim (2012) further studies the TKC hypothesis and provides some empirical evidence of the U-shaped curvilinear relationship between household income inequality and all output indicators of technological development included in a panel regression. Leoncini (2017) also reports significant nonlinearity between innovation and inequality based on comprehensive analysis of a panel data consisting of 148 countries over 1963-2012. In a case where innovation is proxied by input measures such as R&D expenditures, the relationship takes an inverted U-shaped form. The opposite occurs when innovation is measured with patent indicators as an output measure of innovations, i.e., the relationship is negative at low level of patent activity and positive at higher levels of patent activity. Recent research by Gravina and Lanzafame (2021) suggests a U-shaped relationship between innovation and inequality. Unlike numerous studies, Gravina and Lanzafame (2021) categorize innovation into investment-specific technological (IST) change and general-purpose technology. While the latter was shown to have mixed results, IST provides robust evidence of significant nonlinear effect on distribution of disposable income. Following Krusell et al. (2000) they measure IST change as a decline in a relative price of investment goods and find that when the relative price falls below 0.81, technological progress is associated with increase in income inequality, but when the relative price exceeds the threshold value, technological progress is shown to reduce income inequality. In particular, they report that most of emerging economies have positive relationship between technological progress and income inequality while evidence for advanced economies is mixed. They also find that financial development and globalization affect income inequality nonlinearly.

Overall, empirical literature shows that there are many determinants that may affect innovation-inequality nexus. However, most of the papers do not consider nonlinearity and threshold effects between innovation and income inequality, and how the level of technological development can affect role of other determinants of inequality. This paper contributes to the literature addressing these gaps and providing evidence of significant nonlinearities and presence of the U-shaped TKC in the innovation-inequality nexus.

3. METHODOLOGY

3.1. Econometric Issues

Estimating the impact of innovation on income inequality is complicated by a number of challenges. First of all, theory is not clear about which framework to use to describe the relationship between innovation and inequality. To address the model uncertainty problem this study follows a large number of empirical studies on innovation-inequality nexus and on determinants of income inequality. Much of the literature stems from the Kuznets curve framework which suggests the inverse U-shape relationship between income and inequality, and include additional factors based on data availability and authors' priorities. Recent study of the robustness of multiple factors affecting income inequality provides evidence that globalization, technological change, financial and economic development are among the most relevant drivers of income inequality within countries (Ostry and Furceri, 2019). I adopt these findings when formulating the econometric model.

Secondly, the panel data used in this paper is heterogenous in terms of effect of variables of interest on income inequality and in terms of unobserved individual effects. The latter is an inherent attribute of a diverse panel data with countries that have different levels of development and institutions. First differencing takes care of the time-invariant unobserved heterogeneity but leads to a problem of endogeneity between transformed autoregressive variables and an error term (Nickell, 1981). The common way to deal with this problem is to instrument transformed autoregressive variable with earlier lags like in Arellano-Bond (1991).

Another issue to be addressed is potential endogeneity problem caused by a reverse causality between income inequality and some of its determinants, such as economic growth and innovations. Tselios (2011) and Mnif (2016) provide empirical evidence of the reverse causality between innovation and income inequality for European Union and developed countries respectively. According to Rodrı´guez-Pose and Tselios (2010), level of income inequality can act as an incentive or a detriment to innovative activities depending on interaction between dynamic market size and dynamic price effects. If market size dynamics prevails, then less inequality may stimulate innovative activity as it leads to bigger markets for new products. At the same time, when price effect becomes more prevalent, higher income inequality might incentivize innovation because new and expensive technology requires relatively rich consumers (Bertola et al., 2006; Rodrı´guez-Pose and Tselios, 2010; Foellmi and Zweimuller, 2017). Additionally, there is growing empirical literature that finds significant effect of inequality on economic growth (Cingano, 2014; Neves et al., 2016). In particular, Cingano (2014) summarizes empirical literature on inequality-growth nexus and reports that most of the studies find mixed but significant effect of inequality on growth. To deal with potential endogeneity of regressors, Seo and Shin (2016)'s model takes use of the FD-GMM estimator.

Last but not least, another issue is persistence of income inequality which is often ignored in previous studies. It was confirmed in both theoretical and empirical literature that income inequality is history-dependent. In empirical studies, Gravina and Lanzafame (2021) verify that income inequality is a highly persistent variable with all three lags being statistically significant in their baseline model. In theoretical literature, Mookherjee and Ray (2003) build a dynamic model to show the role of occupational diversity in explaining the history-dependence of inequality. Simply put, the poor are unable to catch up with the rich. It justifies the use of dynamic panel framework to take the persistence of inequality into account.

3.2. Estimation Strategy

This study adopts a dynamic panel threshold model developed by Seo and Shin (2016) and made practical by Seo et.al. (2019). It is a novel method that extends Caner and Hansen (2004)'s static panel threshold model by allowing dynamics and relaxing exogeneity assumptions for regressors and a threshold variable. Unlike previous panel threshold models that assume exogeneity (Hansen 1999) or address endogeneity partially (Caner and Hansen, 2004; Kremer et al., 2013), this model deals with endogenous threshold and regressors simultaneously employing first-difference GMM estimation.

Following Seo and Shin (2016), the dynamic threshold model is specified as follows:

$$y_{it} = (1, x'_{it})\phi_1 1\{q_{it} \leq \gamma\} + (1, x'_{it})\phi_2 1\{q_{it} > \gamma\} + \alpha_i, \tag{1}$$

where subscripts i,t indicate number of groups and time period respectively. Number of years of observations is assumed to be fixed while number of groups is approaching infinity; x_{it} is a $k_1 \times 1$ vector of time-varying regressors that also includes y_{it-1} to account for the persistence of a dependent variable, y_{it}; $1\{\cdot\}$ is the indicator function taking on unit or zero values depending on whether a threshold variable q_{it} larger or less than a threshold value γ; ϕ_1 and ϕ_2 are slope coefficients in low and high regimes respectively. Compound error term consists of unobserved individual fixed effects, α_i, and a zero mean idiosyncratic error term, u_{it}, which is assumed to be a martingale difference sequence with a natural filtration F_t:

$$E((u_{it}|F_{t-1}) = 0$$

meaning that expectation of a random disturbance at time t with respect to its past values is zero. However, E $(u_{it}x_{it})$ and E $(u_{it}q_{it})$ need not to be zero, which allows the regressors and the threshold variable to be endogenous. Another source of endogeneity in the model is a correlation between heterogenous fixed effects, α_i, and regressors. To deal with this problem, fixed effects are eliminated through first-difference transformation:

$$\Delta y_{it} = \beta' \Delta x_{it} + \delta' X'_{it} 1_{it}(\gamma) + \Delta u_{it}, \tag{2}$$

where $\beta' = (\phi_{12}, \dots, \phi_{1k_1+1})$, $\delta = \phi_2 - \phi_1$, $X'_{it} = ((1, x'_{it}), (1, x'_{it-1}))$, $1_{it}(\gamma) = \begin{pmatrix} 1\{q_{it} > \gamma\} \\ -1\{q_{it-1} > \gamma\} \end{pmatrix}$.

However, first-difference transformation leads to a downward biased OLS estimator because of correlation between transformed variables Δx_{it} and a differenced error term Δu_{it} (Nickell, 1981). To deal with the endogeneity, first-differenced variables are instrumented by their earlier lags at levels, and parameters $\theta = (\beta', \delta', \gamma)'$ are estimated with FD-GMM estimator like in Arellano and Bond (1991). To apply FD-GMM, consider the following l-dimensional vector of sample moment conditions:

$$\bar{g}_n(\theta) = \frac{1}{n}\sum_{i=1}^{n} g_i(\theta),$$

where $g_i(\theta) = \begin{pmatrix} z_{it_0}(\Delta y_{it_0} - \beta' \Delta x_{it_0} - \delta' X'_{it_0} 1_{it_0}(\gamma)) \\ \vdots \\ z_{iT}(\Delta y_{iT} - \beta' \Delta x_{iT} - \delta' X'_{iT} 1_{iT}(\gamma)) \end{pmatrix}$

with $(z_{it_0,\dots,}z_{iT})'$ being a $l \times 1$ vector of instruments with $2 < t_0 \leq$ T and $l \geq k$ such that $E(\Delta u_{it}|z_{it}) = 0$, for each $t = t_0, \cdots, T$. Since threshold variable is allowed to be endogenous, $(\Delta u_{it}|q_{it}) \neq 0$, and so q_{it} is not included as an instrument. Next step is to construct a GMM criterion function with a positive weight matrix W_n[1]

$$\bar{J}_n(\theta) = \bar{g}_n(\theta)' W_n \bar{g}_n(\theta).$$

Then the GMM estimator is given by $\hat{\theta} = \mathrm{argmin}_{\theta \in \Theta} \bar{J}_n(\theta)$ that minimizes the weighted sum of squares of covariances between instruments and error term. Since the objective GMM function is not continuous in γ, minimization procedure is performed through the grid search algorithm. For each threshold value γ, let

$$\bar{g}_{1n} = \frac{1}{n}\sum_{i=1}^{n} g_{1i} \text{ and } \bar{g}_{2n}(\gamma) = \frac{1}{n}\sum_{i=1}^{n} g_{2i}(\gamma),$$

where $g_{1i} = \begin{pmatrix} z_{it_0}\Delta y_{it_0} \\ \vdots \\ z_{iT}\Delta y_{iT} \end{pmatrix}$ and $g_{2i}(\gamma) = \begin{pmatrix} z_{it_0}(\Delta x_{it_0}, X'_{it_0} 1_{it_0}(\gamma)) \\ \vdots \\ z_{iT}(\Delta x_{iT}, X'_{iT} 1_{iT}(\gamma)) \end{pmatrix}$.

Then, for any fixed γ, the GMM estimator of β and δ is given by

$$\left(\hat{\beta}(\gamma), \hat{\delta}(\gamma)\right)' = (\bar{g}_{2n}(\gamma)' W_n \bar{g}_{2n}(\gamma)^{-1} \bar{g}_{2n}(\gamma)' W_n \bar{g}_{1n}.$$

Finally, a set of parameters $\theta = (\beta', \delta', \gamma)$ is obtained by

$$\hat{\gamma} = \mathrm{argmin}_{\gamma \in \Gamma} \bar{J}_n(\gamma), \text{ and } \left(\hat{\beta}', \hat{\delta}'\right)' = \left(\hat{\beta}'(\hat{\gamma}), \hat{\delta}'(\hat{\gamma})\right)'.$$

In practice, the minimization of the GMM objective function might be numerically intensive when number of observations is large and the threshold variable varies a lot. Like in Hansen (1999), the common practice is to eliminate largest and smallest percentile and search for a threshold, $\hat{\gamma}$, among remaining values. In other words, $\gamma \in \Gamma$, where $\Gamma = [\underline{\gamma}, \overline{\gamma}]$ with $\underline{\gamma}$ and $\overline{\gamma}$ being lower and upper percentiles of a threshold variable, q_{it}. In this study, observed values of a threshold variable are divided into 400 grid points, and the grid search starts at 0.1 quantile and ends at 0.9 quantile of the grid points.

Based on the suggested by Seo and Shin (2016) method, review of the literature on determinants of within-country income-inequality and innovation-inequality nexus, the econometric model (1) in this study is specified as follows:

[1] Refer to Seo and Shin (2016) to see more on how to find an optimal weight matrix W_n.

$$INQ_{it} = \left(\beta_{01}INQ_{i,t-1} + \beta_{11}INN_{it} + \sum_{j=2}^{n}\beta_{j1}X_{jit}\right)1\{INN_{it} \leq \gamma\}$$
$$+\left(\beta_{02}INQ_{i,t-1} + \beta_{12}INN_{it} + \sum_{j=2}^{n}\beta_{j2}X_{jit}\right)1\{INN_{it} > \gamma\} + \alpha_i + u_{it}, \quad (4)$$

where the dependent variable, INQ, is estimated with Gini index for market income; INN is the independent variable of technological change measured by one of the three different proxies: relative price of investment goods, patent applications per a million of population and patent grants per a million of population; γ – a certain threshold value of a variable of innovation; X is a set of control variables which includes real GDP per capita, trade openness, financial development index, level of inflation, share of population aged 65 and above, private credit as a share of GDP, human capital index.

As many studies have found significant effects of income inequality on economic growth (Neves et al., 2016; Cingano, 2014) and technological change (Rodrı´guez-Pose and Tselios, 2010; Tselios, 2011; Foellmi and Zweimuller, 2017), there are strong concerns over simultaneous causality between innovations and income inequality and economic growth and income inequality in the literature. Taking the findings of previous studies into consideration, real GDP per capita and innovations are treated as endogenous variables in the model, while the rest of the regressors are treated as exogenous variables.

Thus, application of Seo and Shin (2016)'s method to investigate nonlinearity and threshold effects in the innovation-inequality nexus allows to address persistence of a variable of income inequality, simultaneous causality between inequality and innovations, potential endogeneity of other determinants of the income inequality included in the model, as well as unobserved heterogeneity in the panel and relatively short period of observations for some of the variables.

3.3. Bootstrap Linearity Test

It is important to test whether the estimated threshold is statistically significant. Following Seo et al. (2019), nonlinearity and threshold effect within the proposed model are tested based on the bootstrap linearity test. Procedure consists of testing the null hypothesis: $H_0: \delta = 0$, for any $\gamma \in \Gamma$, against the alternative hypothesis H_1: $\delta \neq 0$, for some $\gamma \in \Gamma$, where δ is a threshold parameter from the model specification (2), and γ is a threshold value from a set of all possible values of $\gamma \in \Gamma$, where $\Gamma = [\underline{\gamma}, \overline{\gamma}]$. The Seo and Shin (2016)'s method guarantees that estimators are asymptotically normal, which predicates the use of Wald test for statistical inference about estimators including threshold. Null hypothesis is tested with a supremum type statistic as follows

$$sup\mathcal{W} = \sup_{\gamma \in \Gamma} \mathcal{W}_n(\gamma),$$

where $\mathcal{W}_n(\gamma)$ is the standard Wald statistic, i.e., $\mathcal{W}_n(\gamma) = n\hat{\delta}'(\gamma)(\widehat{\Sigma_\delta}(\gamma))^{-1}\hat{\delta}(\gamma)$, where $\widehat{\Sigma_\delta}(\gamma)$ is a consistent asymptotic variance estimator from Seo and Shin (2016)'s asymptotic theory for FD-GMM estimator. As in Seo and Shin (2019), i.i.d. bootstrap algorithm includes a random draw $\{\eta_i\}_{i=1}^{n}$ and estimating $\hat{\delta}(\gamma)*$ like in (3) by replacing Δy_{it} with $\Delta y_{it}^* = \Delta\widehat{u_{it}}\eta_i$, where $\Delta\widehat{u_{it}}$ is the error term from the original sample. Next step is to compute a bootstrap statistic $\mathcal{W}_n^*(\gamma)$ and find $\sup_{\gamma \in \Gamma} \mathcal{W}_n^*(\gamma)$. Final step is to repeat this procedure for a certain number of bootstrapping and find a bootstrap p-value as a proportion of $sup\mathcal{W}_n^*$ that is larger than supremum of original Wald statistic, $\mathcal{W}_n$. If bootstrap p-value is less than 5% then the null hypothesis is rejected providing support that the estimated threshold is statistically significant.

4. DATA AND DESCRIPTION OF VARIABLES

All models estimated in this study are based on a panel data consisting of 72 countries (listed in the Table A1 in the Appendix), over 1994-2017 years. Panel data is almost equal split between high-income and middle-income countries: 39 high-income countries and 33 middle income countries (19 upper middle-income countries, 14 lower middle-income countries). It reflects the fact that this study is aiming to analyze the divergence in income inequality trend between high-income and middle-income countries. Low-income countries are excluded because of missing values and low-quality data on innovative activity. Time span is averaged in 8 three-year periods to reduce short-term fluctuations, possible measurement errors and, at the same time, maximize number of observations within chosen time period. In order to avoid issues related to missing data and find a balance between time-series and cross-sectional dimensions for all regressors included in the model, I start observations from 1994. This period includes onset of the divergence in the income inequality trend of high-income countries with middle-and low-income countries that becomes obvious in the early 2000s (Fig. 1). All variables are reported in summary statistics (Table 1).

Historical data about within-country income inequality was obtained from the Standardized World Income Inequality Database (Solt, 2019), which contains Gini index' estimates for market and disposable income collected from OECD data base, World Bank, National statistical offices and other sources including academic studies. Gini index for market income is used to measure income distribution before taxes and transfers, i.e., without redistribution policy effects. Thus, using market income instead of disposable income allows to estimate "pure" effect of innovations on inequality within countries.

Taking into account the complexity of technological process, there is no optimal measurement for innovation outputs. The choice of an appropriate proxy depends on type and mechanism of technological change. This study focuses only on those indicators that measure output of innovative activity. Therefore, such measures like expenditures on R&D and number of researchers are not included in this study.

Table 1. Summary Statistics (N=72, T=1994-2017)

Variable	Unit of Measurement	No of observations	Mean	St. Deviation	Min	Max
Gini Index	0-100 Scale	576	45.990	6.403	21.830	72.270
RGDP per capita	US$ at chained PPPs (in thousands, 2017 prices)	576	23.512	17.660	1.548	90.365
Relative Price of Investment Goods	Price Ratio	576	1.096	0.319	0.593	2.570
Patent Applications/ Population	No. of applications per 1 ml. of population	576	165.100	412.000	0.184	3,203
Patent Grants/Population	No. of grants per 1 ml. of population	549	76.200	199.900	0.021	1,834
Financial Development Index	0-100 Scale	576	45.420	23.460	5.181	98.230
Domestic Private Credit to GDP	% of GDP	573	65.870	48.010	0.777	242.800
Trade Openness	% of GDP	575	88.110	63.730	16.820	433.100
CPI	Annual %	563	15.640	82.250	-2.776	1,189
Population 65 and above	% of total population	576	11.460	5.085	1.945	26.020
Human Capital Index	-	560	2.870	0.526	1.450	3.814

Based on much of the literature, skill-biased technological change is one of the key mechanisms behind the influence of innovations on income inequality. That is why among many different types of innovations this paper focuses on innovations that are more likely to create skill-premium as a relative increase in wages of the skilled labor over the unskilled labor. As was shown by Krussel et al. (2000), investment specific technologies (IST) increase the demand for skilled workers through capital-skill complementarity leading to growth of the skill-premium that affects income inequality. Following Krussel et al. (2000), Hui (2012) also quantitatively demonstrates that investment-specific technological change is a key element that drives skill premium. Therefore, IST is used as a core category of innovations in the model. In order to proxy for IST, I calculate the relative price of investment goods as a ratio between price level of the capital formation to the price level of the household consumption from the Penn World Table (PWT; Feenstra et al., 2015), where price levels for each country are estimated relative to price level of USA output-side GDP in 2017. The decrease in the relative price of investment goods (price of capital formation) is associated with the increase in the investment-specific technological innovations. Specifically, Krussel et al. (2000) use national data on investment in equipment in the US to show that technological advances make new equipment cheaper resulting in growth of equipment quantity. Indeed, if we look at costs of technologies over time, we will see consistent and rapid decline in the costs which makes new technologies more available and widespread (Figure A1 in the Appendix). Higher affordability of capital and digitalization of businesses are among the forces that cause the decoupling between productivity and labor incomes (Bernstein and Raman, 2015). As a result, technological change is expected to shift income from labor to capital reducing labor share in aggregate income and increasing returns for capital owners. Other researchers like Jovanovic and Rousseau (2005), and Karabarbounis and Neiman (2014) also used decline of relative price of technologies as an indicator of technological progress. Thus, countries with reducing relative prices of investment goods are expected to have higher level of technological development than countries with lower pace of relative price reduction or with increase in the relative price of investment goods.

It should be noted that relative price of investment goods does not only reflect investment specific technological change but also policy component. There is a substantial body of literature that highlights the importance of institutions and economic policy in the process of capital accumulation (Olson, 1996; Taylor, 1997). According to Restuccia and Urrutia (2001), relative price of investment is affected by fiscal policy, taxation and trade restrictions. However, changes in policies and tax rates across years are relatively small to affect capital accumulation in a major way.

For the purpose of robustness check, number of patent applications and patent grants weighted by total population were used as alternative proxies for innovations in the model. Both indicators of patent activity were retrieved from WIPO data base for PCT patents applications and grants by resident. Total population data was retrieved from Penn World Table. Although measurement of the patent activity is the most common proxy of innovation output in literature, not all inventions are patented, and as was noticed by Singh et al. (2021), not all patents reflect technological development. Because of mentioned drawbacks, patent indicators are not used as a benchmark measurement for innovations in further analysis.

As innovation is not the only significant factor that can disrupt income distribution, other drivers of inequality should be taken into account to get a better view on the innovation-inequality nexus. According to most of the studies, technological change, trade globalization and financial development play significant role in income distribution (Furceri and Ostry, 2019; Nolan et al., 2019; Milanovic, 2016). In most of empirical literature on the finance-innovation nexus, financial sector development is measured with two indicators of financial depth – share of private credit in GDP and stock market capitalization to GDP. However, this approach does not take into account multidimensionality of the financial sector development. This study adopts a more comprehensive index – financial development index retrieved from IMF Financial Development Data base. Besides a dimension of financial depth, financial development index also consists of access and efficiency dimensions for both financial institutions and financial markets. Trade integration is proxied by sum of imports and exports of goods and services as a share of GDP from World Bank Development Indicators. Finally, economic development is measured by real GDP per capita as a standard practice in the literature. Real GDP per capita was calculated based on real GDP and population data retrieved from Penn World Table.

To check the robustness of the results, the model specification is extended by adding additional control variables that are also considered to be determinants of income inequality in empirical literature. In particular, ratio of private credit to GDP, human capital index, consumer price index and share of population aged 65 and above are included as potential factors affecting income inequality. Private credit to GDP ratio, extracted from Financial Structure Data Base (Beck et al., 2000), is used as an alternative measure of financial development. Retrieved from PWT, human capital index estimates return to education based on Mincer equation. Consumer price index and share of population aged 65 and above were extracted from World Development Indicators to take into account inflation and demographical component respectively.

5. MAIN FINDINGS

Table 2 reports the results of the dynamic panel model with innovations being endogenous transition variable and real GDP per capita being an endogenous regressor. Model 1 (M1) is a baseline model where innovation is measured by changes in the relative price of investment goods, and 3 other determinants of income inequality are included: real GDP per capita, financial development index and trade openness. Findings of model 1 show that before reaching a threshold value of 0.97 (left side of the U-shaped TKC), relative price of investment goods and income inequality have negative relationship, meaning that increasing relative price of investment goods leads to lower income inequality. Note that since changes in the relative price of investment goods is a proxy for investment specific technological change, it means that technological advancement, associated with decrease in relative price of investment goods, leads to incrementally larger income inequality. In contrast, countries that have high relative prices of investment goods beyond threshold value (right side of the U-shaped TKC) have positive relationship between relative price of investment goods and Gini index.

Table 2. Results from Dynamic Panel Model with Threshold and Endogeneity. Dependent Variable is Gini Coefficient for Market Income

	Proxy for Innovation		
	Rel. Price of Inv. Goods (M1)	Patent Appl./Population (M2)	Patent Grant/Population (M3)
	Below Threshold	**Below Threshold**	**Below Threshold**
Lag of Gini Index	0.636***	0.653***	0.633***
	(0.015)	(0.012)	(0.015)
Innovation	-3.639***	-0.015***	-0.039***
	(0.463)	(0.003)	(0.007)
RGDP per capita	-0.033***	-0.032***	-0.088***
	(0.004)	(0.005)	(0.009)
Financial Development	0.009***	0.017***	-0.027***
	(0.003)	(0.003)	(0.007)
Trade Openness	0.014***	0.003***	-0.005**
	(0.001)	(0.001)	(0.002)
	Above Threshold	**Above Threshold**	**Above Threshold**
Lag of Gini Index	-0.123***	0.028***	-0.015
	(0.023)	(0.007)	(0.015)
Innovation	4.413***	0.015***	0.039***
	(0.428)	(0.003)	(0.007)
RGDP per capita	0.053***	0.054***	0.102***
	(0.008)	(0.005)	(0.009)
Financial Development	-0.000	-0.020***	0.000
	(0.006)	(0.003)	(0.008)
Trade Openness	-0.004***	-0.008***	0.014***
	(0.001)	(0.001)	(0.002)
Threshold value	0.970***	96.680**	30.110***
	(0.023)	(39.140)	(4.768)
Upper Regime (% of observations)	61%	38%	54%
95% Confidence Interval	[0.926 - 1.015]	[61.567 - 131.797]	[20.760 - 39.451]
Bootstrap p-value for Linearity Test	0.0	0.0	0.0
Groups	72	71	64
Observations	576	568	512

Note: ***, **, * denote statistical significance level at 1%, 5% and 10%, respectively.

In this case, technological advancement leads to decline in income inequality. It should be noted that this decline becomes progressively smaller as relative price approaches threshold. After the relative price becomes lower than the threshold, innovations that lead to a decline of the relative price even further start contributing to widening income inequality. This switch between positive and negative relationships could be explained by trade-off between positive and negative effects of technology on wages, labor productivity and labor shares in income. In a case where labor-substituting effects and skill premium effect of technological change prevails over effects that improve labor productivity and raise labor incomes, we observe technology-induced income inequality (Dao et al., 2017; Acemoglu and Autor, 2011). As follows from the U-shaped relationship between innovations and inequality, countries with high level of technological development reflected by the fall in the relative price of investment goods are more likely to have innovation-induced inequality in comparison to less technologically advanced countries.

Models 2-3, which are built for different proxies of innovation, also provide support for the U-shaped relationship between innovations and income inequality. Interpretation of findings in the models where innovation is proxied by indicators of patent activity are more straightforward. Countries with higher level of technological development are located on the right side of the U-shaped TKC, while less technologically advanced countries located on the left side of the curve. Interestingly, the results of models 1-3 also support the augmented KC hypothesis suggested by Galbraith et al. (2000). They provide empirical evidence that inequality-growth relationship follows the original inverted U-shaped KC at the lower levels of economic development. However, as a result of technological change, countries with high level of economic development follow the U-shaped augmented KC. This pattern falls under Mark 1 and Mark 2 innovations in the Schumpeterian framework. Since middle-income countries tend to be less technologically developed, imitation and adoption are prevailing forms of innovation (Cirera and Maloney, 2017). Imitative behavior erodes innovators' rents leading to reduced inequality. However, at the later stages of technological development, innovation activity is more concentrated and entry barriers are higher because innovation becomes more R&D intensive, thus increasing innovators' rents and income inequality (Malerba and Orsenigo, 1996). It is evident from the first look at the trend of income inequality for high-income countries. According to the Gini coefficient, their inequality has been rising more than in other income categories.

Note that in all models, lagged Gini index is statistically significant, justifying the use of the dynamic panel framework and GMM estimation technique. As for other determinants of income inequality, only model 2 provides evidence of nonlinearity between financial development and income inequality with relation to technological progress. In model 2, relationship between financial development and income inequality supports the financial Kuznets curve hypothesis about inverted U-shaped relationship in the finance-inequality nexus inferred from theoretical predictions of Greenwood and Jovanovic (1990) and the empirical work of Nikoloski (2013).

Table 3. Results from the Dynamic Panel Threshold Model with Additional Control Variables. Dependent Variable Is Gini Coefficient for Market Income.

	Model 4	Model 5	Model 6	Model 7
	Below Threshold	**Below Threshold**	**Below Threshold**	**Below Threshold**
Lag of Gini Index	0.696*** (0.015)	0.637*** (0.020)	0.691*** (0.018)	0.634*** (0.015)
Innovation	-4.801*** (0.460)	-5.316*** (0.631)	-5.237*** (0.487)	-2.331*** (0.984)
RGDP per capita	-0.024*** (0.003)	0.001 (0.004)	-0.018*** (0.003)	0.006 (0.004)
Financial Development		0.022*** (0.0035)	0.012*** (0.0041)	-0.022***(0.0063)
Trade Openness	0.001 (0.001)	0.004*** (0.001)	0.004*** (0.001)	0.002** (0.001)
Private Credit/GDP	0.007*** (0.001)			
HC index		-2.024*** (0.234)		
Aging			-0.020 (0.016)	
CPI				0.109*** (0.015)
	Above Threshold	**Above Threshold**	**Above Threshold**	**Above Threshold**
Lag of Gini Index	-0.107*** (0.019)	-0.037* (0.019)	-0.136*** (0.024)	-0.004 (0.015)
Innovation	4.933*** (0.510)	4.132*** (0.695)	4.684*** (0.435)	2.042*** (0.993)
RGDP per capita	0.040*** (0.009)	0.041** (0.018)	0.031*** (0.009)	-0.017*** (0.002)
Financial Development		-0.027*** (0.007)	-0.011** (0.005)	0.025*** (0.007)
Trade Openness	0.001** (0.000)	0.007*** (0.002)	-0.003*** (0.001)	0.000 (0.000)
Private Credit/GDP	-0.012*** (0.002)			
HC index		1.970*** (0.271)		
Aging			-0.048** (0.021)	
CPI				-0.111*** (0.015)
Threshold value	0.9740*** (0.018)	1.137*** (0.024)	0.984*** (0.029)	0.884*** (0.026)
95% Confidence Interval	[0.939 - 1.008]	[1.091 - 1.183]	[0.926 - 1.041]	[0.807 - 0.961]
Bootstrap p-value for Linearity Test	0.0	0.0	0.0	0.0
Groups	71	69	71	70
Observations	568	552	568	560

Note: Innovation is proxied by relative price of investment goods. ***, **, * denote statistical significance level at 1%, 5% and 10%, respectively.

According to the results, at lower level of technological development, which is also associated with lower level of economic development, financial development contributes to widening income inequality as limited number of people are exposed to new financial opportunities. When countries achieve higher level of technological development, financial intermediaries become widely accessible by majority of the population which is associated with lower income inequality. With respect to trade openness, the results are ambiguous. The findings in models 1-2 are consistent with inverse U-type Openness Kuznets curve established in previous studies. For example, Dobson and Ramlogan (2009) provide evidence of inverse U-shape relationship between trade openness and income inequality in countries of Latin America, Jalil (2012) comes to the same result for a case of China. However, Topuz and Dagdemir (2020) find U-shape curvilinear relationship in the trade-inequality nexus for a case of Turkey. The findings of model 3 also suggests U-shaped relationship between trade openness and inequality as countries become more technologically advanced.

Further analysis is focused on extending the baseline model 1 with additional control variables: human capital index, inflation, share of population over 65 years old. Also, financial development index is substituted with private credit as a share of GDP, a proxy that is frequently used to estimate financial sector development in the empirical literature (Law et al., 2020; Gravina and Lanzafame, 2021). The ratio of private credit to GDP is obtained from Financial Structure Data Base (Beck et al., 2000 (updated Sep 2019)). Human capital index is extracted from Penn World Table and measured based on average years of schooling and rate of return to education as estimated by Mincer equation. It is added because educational attainment and rate of returns to education determine supply and demand of educated workers which affect distribution of earnings (Mincer, 1958; Becker and Chiswick, 1966). It means that the impact of human capital on income inequality depends on distribution of education and evolution of returns to education. The latter determines the skill premium and directly depends on technological change. Next, the baseline model is estimated with an addition of demographic variable. Since Gini index is calculated for total population, it is important to incorporate demographic indicators accounting for age structure. Based on the facts that advanced countries tend to have higher share of elderly people and population aging is found to decline the labor share in total income (Wang et al., 2017), a share of population over 65 is included as additional control variable. Finally, because positive inflation tends to exert a positive effect on increase in inequality (Albanesi, 2007), consumer price index (CPI), extracted from World Development Indicators, is also included in the baseline model.

Augmenting the baseline model by including additional covariates, such as human capital index, inflation and share of population aged over 65, does not affect the main findings about the effects of technological progress on income inequality (Table 3). Innovations play the same role in reducing income inequality in less technologically advanced countries and increasing inequalities in more technologically advanced countries. However, threshold value is sensitive to including additional control variable and varies in 0.88-1.14 interval. At the same time, nonlinearity is robust. Results of the bootstrap linearity test confirms significant nonlinearity in innovation-inequality nexus. As for other determinants, findings vary across models 4-7. Level of income, as measured by real GDP per capita, follows U-shaped curve in models 4 and 6. However, including inflation (Model 7) or human capital index (Model 5) makes effects of economic development statistically insignificant for less technologically developed countries, and mixed for technologically advanced countries. Changing a proxy for financial development from comprehensive index of financial development to share of private credit does not change the inverted U-shaped relationship between financial development and income inequality found in the baseline model. But including inflation in the model 7 alters the signs for a variable of financial development. Finally, trade openness does not provide evidence for significant nonlinearity in regards to level of technological development.

Regarding additional control variables, the effect of human capital on income inequality is positive when investment specific innovations cause relative price of investment goods to fall lower than the threshold. Whereas effect is negative when the same happens in countries with lower technological development. Possible explanation behind this relationship could lie in the difference in equality of education distribution observed in advanced and emerging economies included in the panel. As was argued by Becker and Chiswick (1966), income inequality is positively associated with education inequality. Moreover, average years of schooling can have positive or negative effects on income inequality. According to Jaumotte et al. (2013), an increase in a number of graduates with secondary or higher education tends to widen income inequality. As for effect of aging on inequality, aging is found statistically significant (at 10%) only when relative price of investment goods is above the threshold, and carries negative effect on inequality. The exact mechanism behind these effects would require further research incorporating intricate sociodemographic factors. Finally, inflation shows inverted U-shaped relationship with inequality. It corresponds to the findings of Monnin (2014), rising inflation is associated with decreasing income inequality in countries that have low initial inflation, and with increasing inequality in countries that have high initial inflation. Indeed, most of the countries with pre-threshold values of relative price of investment goods are advanced countries with low initial inflation, and most of the countries with post-threshold values have high inflation.

6. ROBUSTNESS CHECK

In order to further estimate the robustness of the results to different methods, estimation strategy is modified. Instead of estimating dynamic panel with endogenous threshold, I estimate the following dynamic quadratic model:

$$\begin{aligned} INQ_{it} = {} & \beta_0 INQ_{i,t-1} + \beta_0 INQ_{i,t-2} + \beta_1 INN_{it} + \beta_2 INN_{it}^2 + \beta_3 RGDPC_{it} \\ & + \beta_4 RGDPC_{it}^2 + \beta_5 FD_{it} + \beta_6 FD_{it}^2 + \beta_7 TO_{it} + \beta_8 TO_{it}^2 + \beta_9 X_{it} + \alpha_i \\ & + \mu_t + u_{it}, \end{aligned} \tag{5}$$

where INQ indicates Gini index for market income, INN – innovations proxied by relative price of investment goods, FD is financial development index, TO is trade openness, and X is a set of additional control variables like in the baseline model (share of private credit in GDP, human capital index, inflation, share of population aged 65 and above); α_i, μ_t, u_{it} are individual fixed effects, time dummies, and idiosyncratic error term, respectively.

In model specification (5), the nonlinear effect is captured by squared terms for main determinants of income inequality. It is a common way to include nonlinearity in empirical literature, but it has limitations. First of all, including square terms could cause multicollinearity in the model (Narayan and Narayan, 2010). In the STATA module, xtabond2, that was used to estimate Equation (5), variables with correlation coefficient of 1 are dropped from estimation due to multicollinearity. Even though squared terms were not removed by multicollinearity, they are highly correlated. Therefore, standard errors should be treated with caution. Secondly, it does not account for threshold effects. Although threshold values could be estimated through differentiating the Equation (5) with respect to a variable of interest, other regressors are regime independent by definition. Moreover, search for a turning point using quadratic specification impose an a priori restriction that effect of innovation on inequality is monotonically and symmetrically increases and decreases with the level of technological development. However, it may also be a case that a certain level of technological development should be reached before innovation has any impact on inequality. Despite limitations, this method remains a common and suitable way to investigate potential nonlinearities in the relationship of interest.

Note that, panel data methods such as fixed effects method are not performed because eliminating unobserved time-invariant variables through differencing leads to significant Nickel's bias in dynamic panel models (Nickel, 1981; Judson and Owen, 1999). Instead, Equation (5) is estimated with two-step system GMM (Sys-GMM) method developed by Arellano and Bover (1995), and Blundell and Bond (1998). Two-step Sys-GMM is found to be more efficient and robust to autocorrelation when dependent variable is highly persistent, such as dependent variable in the model[2]. This method differs from previously used difference GMM estimator because Sys-GMM simultaneously estimates both difference and level equations when instrumenting endogenous variables with their lags3. Since Sys-GMM also assumes no correlation between differences used as instruments and error terms, I include time dummies for this assumption more likely to hold (Roodman, 2009).

Table 4 reports results of the newly specified model estimated with two step Sys-GMM and extended with additional control variables and more lags of dependent variable to increase dynamics.

[2] Using Difference GMM in a case of persistent dependent variable can lead to a problem of weak instruments (Blundell and Bond, 1998).

[3] Thus, system GMM combines difference GMM and level equation.

Table 4. Sys-GMM Estimation. Dependent Variable Is Gini Coefficient for Market Income

	Model 8	Model 9	Model 10	Model 11	Model 12
First Lag of Gini	1.554*** (0.181)	1.547*** (0.228)	1.613*** (0.240)	1.471*** (0.229)	1.442*** (0.141)
Second Lag of Gini	-0.740***(0.201)	-0.762***(0.226)	-0.784***(0.230)	-0.679***(0.211)	-0.538***(0.157)
RGDP per capita	-0.0717 (0.0483)	-0.0562 (0.0536)	-0.0687 (0.0531)	-0.0636 (0.0534)	-0.0856*(0.0501)
RGDP per capita squared	0.0009* (0.0005)	0.0007 (0.0006)	0.0001* (0.0005)	0.0006 (0.0006)	0.0011*(0.0006)
Innovation	-3.244* (1.634)	-5.156** (2.485)	-3.425* (1.731)	-4.826** (2.150)	-3.184*(1.824)
Innovation squared	1.047** (0.484)	1.634** (0.734)	1.088** (0.509)	1.276* (0.654)	0.959* (0.540)
FD index	0.066 (0.044)	0.063 (0.044)	0.059 (0.050)	0.048 (0.041)	
FD index squared	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	
Trade Openness	-0.005 (0.006)	-0.002 (0.010)	-0.002 (0.010)	-0.008 (0.006)	-0.004 (0.004)
Trade Openness squared	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
HC index		-0.712 (1.090)			
Aging			-0.055 (0.134)		
CPI				-0.009 (0.022)	
Private Credit/GDP					0.031* (0.017)
Private Credit/GDP^2					-0.0001* (0.0000)
Time Effects	YES	YES	YES	YES	YES
AR(1)	0.026	0.035	0.024	0.046	0.023
AR(2)	0.234	0.193	0.314	0.119	0.199
Hansen	0.674	0.642	0.634	0.788	0.414
Instruments	33	33	33	33	33
Prob>F	0	0	0	0	0
Groups	72	70	72	71	72
Observations	431	419	431	422	428

Lind and Mehlum U-test for IST variable proxied by relative price of investment goods
H1: U shape vs. H0: Monotone or Inverse U shape

Lower bound slope	-2.001***	-3.216***	-2.134***	-3.312***	-2.046***
Upper bound slope	2.139***	3.246***	2.168***	1.733	1.745***
Extreme point	1.549	1.577	1.574	1.891	1.660
U-test p-value	0.038	0.030	0.038	0.137	0.050

Note: Innovation is proxied by relative price of investment goods; Fixed effects are removed using forward orthogonal deviation technique to maximize sample size. Windmeijer (2005) finite sample correction for two-step covariance matrix is performed for all models to address possible downward bias in standard errors. Standard errors are clustered at the id level; ***, **, * denote statistical significance level at 1%, 5% and 10% respectively.

According to the second-order autocorrelation AR(2) and Hansen tests, there is no second-order correlation between error terms and the overidentifying restrictions are valid, and so the instruments are consistent. All 5 versions (models 8-12) confirm U-shaped relationship between innovation and Gini index, which is consistent with the baseline model. However, as was pointed out by Lind and Mehlum (2010), the estimated extremum point in the quadratic regression is a week criterion for U-shaped or inverse U-shaped relationship. Because it is also possible that nonlinear relationship is convex and monotonic, therefore, no clear extreme point exists. Following Lind and Mehlum (2010), model specification (5) was tested with Lind and Mehlum U-test (LM U-test) to confirm nonlinearity and statistical significance of U-shaped curvilinear relationship between IST and income inequality.

Based on the LM U-test, the null hypothesis of monotonicity is rejected for all models except the model that includes inflation as an additional covariate (model 11). Thus, almost all findings from Table 4 support hypothesis about U-shape relationship between innovation and inequality. However, it should be noted that when not accounted for threshold effects and using quadratic specification, extreme point is almost twice as high as a threshold found in the baseline model.

Findings of the estimated with Sys-GMM model provide the evidence about the nonlinear U-shaped relationship between technological change proxied by relative price of investment goods and income inequality. At the same time, the model with specification (5) does not find statistically significant effect for other determinants, except a version that uses a share of private credit in GDP instead of financial development index. Only model 12 reports statistically significant U-shaped relationship between economic development and income inequality, and supports the financial Kuznets Curve hypothesis. Thus, there is only limited evidence that other determinants have nonlinear effects with respect to technological progress. However, robustness check with different control variables and different estimation method does not affect significance of the nonlinear relationship between investment-specific technological change and income inequality.

7. CONCLUSION

Applying recently developed dynamic panel model with endogeneity and threshold effects developed by Seo and Shin (2016), I estimate nonlinear effect of innovation on income inequality and find significant U-shaped curvilinear relationship between different measures of innovations and income inequality. To the best of my knowledge, it is the first attempt at applying dynamic threshold model with endogeneity to the innovation-inequality nexus. Results show technological development over the period from 1994-2017 is consistent with the Schumpeter's line of reasoning about innovation that goes through phases of creative destruction and creative accumulation. At the earlier stage of technological development innovations tend to reduce income inequality because entry barriers for innovators are low and new technologies decline share of old industries. However, when country reaches a certain threshold, scale and depth of innovations tend to widen inequality through unequal gains between innovators that can afford high R&D expenses and those who fall behind. Thus, innovations can both reduce and widen income inequality depending on the level of technological development itself. It was shown that technologically advanced countries are more likely to have technology-induced inequalities. The findings confirm both hypothesis about nonlinearity and the U-shaped Technological Kuznets Curve. Technological progress reflected by decline in relative price of investment goods leads to a decline in inequality in countries with low innovative activity and to an increase in inequality in countries with higher innovative activity. Results for innovation-inequality relationship are robust to including additional control variables and changing specification and estimation method from difference GMM to two-step Sys-GMM.

It was also shown that achieving high levels of technological development can change how economic growth and financial development affect income inequality. In countries with relatively low level of technological development, income growth and income inequality have negative relationship as technologies improve. The opposite relationship is observed when countries achieve higher level of technological development. Financial development increases inequality in countries with lower level of technological development and decreases inequality in technologically advanced countries. It is consistent with the inverted U-shaped financial Kuznets curve tested by Nikoloski (2013). Thus, achieving a certain level of technological development is associated with inequality-reducing effect of financial development and inequality-enhancing effect of economic growth. This relationship is robust to including most of the additional control variables. As for trade openness, results are ambiguous and require further research on how innovations influence trade as a determinant of income inequality.

Technological development is a complex and disruptive process that involves difficult transitions. It is important to take into account the potential negative effects of innovations when developing strategies to reduce economic inequality, especially in the case of technologically advanced countries. In order to realize the full potential of innovation for economic growth, policy-makers should promote more initiatives for inclusive innovation-driven growth.

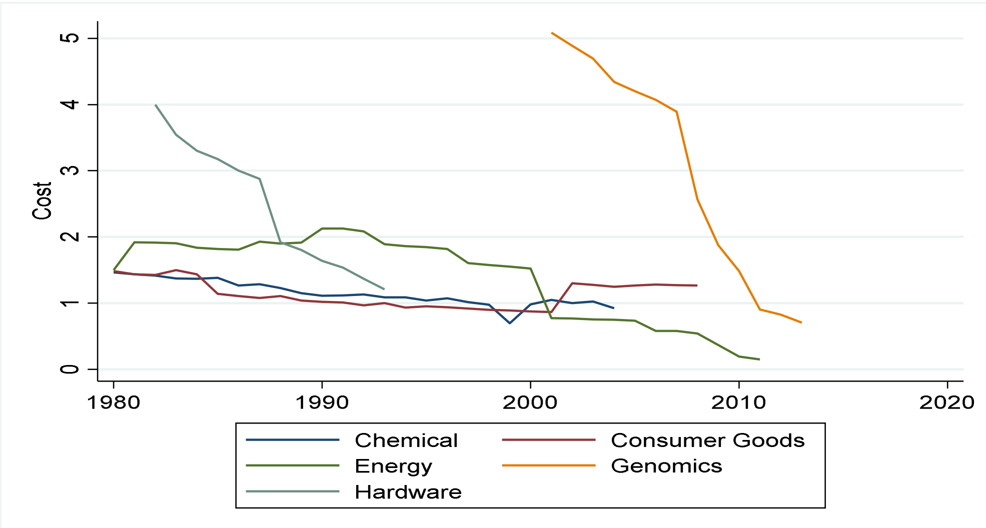
There are many potential extensions of the current study. One might further investigate effect of innovations on inequality via including interaction terms between innovations and potential transmission channels like FDI, human capital, international trade and financial institutions in influencing income inequality. Another potential area of research is to compare how different types of innovations affect income inequality.

APPENDIX

Table A1. List of Countries Included in The Panel Data

High Income	Argentina, Australia, Austria, Belgium, Canada, Chile, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hong Kong, Hungary, Iceland, Ireland, Israel, Italy, Japan, Korea, Latvia, Lithuania, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Singapore, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States, Uruguay
Upper Middle Income	Armenia, Belarus, Brazil, Bulgaria, China, Colombia, Costa Rica, Kazakhstan, Iran, Jamaica, Malaysia, Mexico, Peru, Romania, Russia, South Africa, Thailand, Turkey, Venezuela
Lower Middle Income	Bangladesh, Egypt, Georgia, India, Indonesia, Kenya, Kyrgyzstan, Moldova, Pakistan, Philippines, Sri Lanka, Tunisia, Ukraine, Vietnam

Note: Income groups as defined by World Bank Analytical Classification for 2017 calendar year (World Bank List of Economies, June 2018).



Note: Original data was converted into log scale. Based on the dataset from Farmer and Lafond (2016).

Figure A1. Average Cost of 66 Technologies over 1980-2013

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