What "Causes" Income Inequality?
Technological Innovation versus Financialization[†‡]

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Abstract

This study addresses the question of what causes inequality, between technological innovation and financialization, both of which are commonly regarded as the main factors responsible for increasing income inequality globally. While an increasingly large volume of the literature analyzes the relationship using the cross-country panel data, it tends to be done separately, either analyzing the effect of either innovation or financialization. Further, most are subject to various econometrical issues including endogeneity, and thus a robust causal relationship is not established. This study proposes an empirical model which can address such drawbacks and analyze both impacts in a single framework, so that one may compare the relative importance of the two factors. Specifically, it adopts a structural vector autoregression (SVAR) model with recursive identification on income inequality and economic growth, which are based on neoclassical growth theory. Then, this study applies Jordà's (2005, *American Economic Review*) local projection (LP) approach to the impulse response analysis. Furthermore, in analyzing country panel data, this study introduces panel time-series (i.e., large heterogenous panel) estimation rooted in CCEMG estimator (Pesaran, 2006, *Econometrica*) which covers various econometrical issues of panel data analysis.

First, the results show no statistically significant evidence of innovation aggravating income inequality, which differs from Aghion et al. (2018, *The Review of Economic Studies*) arguing that innovation increases income inequality by protecting the monopolistic rents of incumbent entrepreneurs. The key explanation of such difference is that we consider innovation affecting equity not only through productivity but also through investment, whereas others focused only on the former. Such contribution is rooted in the recursive VAR model allowing feedback effects among all variables. Specifically, this study finds that the response of labor-augmenting productivity to innovation shock is favorable to rich, which is in line with the findings of Aghion et al. (2018), but it is mitigated by the response of capital investment following the productivity factor in the recursive shock structure, which is a novel finding of this study. Second, this study finds that not the variable of financial development (e.g., private credit or liquidity liability ratio to GDP) but financialization variables (e.g., stock market capitalization or volume of stock trade ratio to GDP) aggravates income inequality. In addition, combined with additional analyses on economic growth, the empirical findings of this study indicate that promoting technological innovation is a Pareto-improving policy that it accelerates economic growth without increasing income inequality, whereas financialization worsens income inequality without significantly affecting economic growth.

Keywords: Income inequality, financialization, innovation, panel time-series, structural vector autoregression, and local projections

JEL Classification: O11, O15, O47.

1. Introduction

Despite great interests and necessity toward cross-country determinants of income inequality, there exist relatively fewer related empirical studies than other economics strands, such as applied macroeconomics, namely, business cycle studies or within-country micro-level discussions on income inequality conducted by applied microeconomics or heterogenous agent macroeconomics. Although the studies based on micro-level data have certain comparative advantages in focusing on household- or firm-level labor market, policy effects, and factors related to general equilibrium frameworks, those strands are also limited in discussing country-level macroeconomic institutional factors related to financial sectors or technological innovations, which can be studied by cross-country analysis. However, studies utilizing cross-country (panel) data have been ignored because of the considerable drawbacks in cross-sectional panel analysis with country-level data.

Specifically, the drawbacks in cross-sectional country panel analysis have been summarized by Durlauf (2009), which were the first to criticize the neoclassical empirical growth models (i.e., *growth regression*) but applicable to other cross-country panel analyses, including that on income inequality. Particularly, *endogeneity* (i.e., the model variables are themselves are endogenous) and *model uncertainty* (i.e., the choice of control variables is fundamentally ad-hoc and makes estimation results sensitive to control sets), as discussed by Durlauf (2009), are highly critical that they are enough themselves to undermine the validity of econometrical interpretations. In addition, the methodologies adopted by recent country panel analyses (e.g., panel-fixed effect or dynamic panel GMM model of Berg et al. (2018) and Aghion et al. (2018), and so on) have been barely changed from the ones in mid-1990's or early 2000's (e.g., Islam (1995) and Barro (2000) and so on), whereas the methodologies of other strands of economics continue to advance. The stagnation in empirical methodology seems to be primarily due to the limitations in data availability; for a long time, country panel datasets have a large panel unit (country) dimension but a short (yearly) time span.

Given those shortcomings, the distributional impacts of financialization or technological innovation are limitedly discussed despite recent increasing interests on the subjects. Specifically, cross-sectional panel analyses on the effect of financialization, such as Kwon and Roberts (2015), Dünhaupt (2016), and Alexiou et al. (2021) basically utilized panel fixed-effect model which are susceptible to endogeneity. Moreover, even considering endogeneity by introducing dynamic panel GMM or instrument approaches, the analyses of Kus (2012) and Aghion et al. (2018) on financialization and innovation, respectively, are susceptible to model uncertainty and unable to consider possible feedback effects between regressors. Essentially, given that studies on financialization and innovation utilize different control variable sets depending on their research

interests and data availability, directly comparing the equity impacts of those factors is impossible.

In recent years, however, the (time) accumulation of country panel data enables to introduce panel time-series (i.e., large heterogenous panel) approaches instead of conventional cross-sectional panel ones. As fundamentally rooted in time-series methodologies, panel time-series approaches can address the critiques on the conventional cross-country panel estimations. Particularly, by utilizing structural vector autoregression (VAR) model with recursive identification, identifying exogenous structural shocks orthogonal to each other is possible, and thus can discuss causal effects. In addition, by specifying variables (i.e., transmission mechanisms in structural VAR model) with solid theoretical basis and commonly applicable to various countries, the empirical model of this study can address model uncertainty. Furthermore, this study introduces the local projection (LP) method of Jordà (2005), which can easily derive impulse responses with standard econometric techniques instead of complicating the computation process, such as the MCMC simulation. On the basis of such advantage, this study introduces a panel times-series estimator of Pesaran (2006), which has various econometrical advantages.

Utilizing LP analysis on the panel recursive VAR model, this study finds that technological innovation measured by citation-weighted patent size does not significantly impact income inequality, which contrasts the findings of Aghion et al. (2018) using cross-sectional panel analysis that innovation increases top income shares: The key difference between the two empirical findings seems to be the theoretical scope that this study covers every possible mechanism through national account factors, including capital investment, whereas the model of Aghion et al. (2018) mainly focused on innovation-preserving monopolistic rents. They are also reflected in the differences of empirical approaches between panel recursive VAR and cross-sectional panel specification, of which the former allows feedback effects among variables. Regarding financialization, this study uncovers that financialization measured by the relative size of stock market features to aggregate economy increases income inequality, which is in line with previous studies, such as Kus (2012). Despite that the finding on financialization has already been discussed in other literatures, the contribution of this study is to compare various equity determinants in a single empirical framework, which addresses econometrical issues of conventional cross-sectional panel approaches.

In addition, comparing the equity impact of financialization to that of financial development measured by financial institution features, this study finds that financialization is a key finance feature that aggravates income inequality, given that financial development does not significantly affect top income shares. Moreover, combined with the analysis on the growth effects of financialization and innovation, the empirical findings are indicative of the Pareto-improving effect of technological innovation that promotes economic growth without worsening income inequality. Meanwhile,

financialization is found to be Pareto worsening, given that it seemingly aggravates income inequality with a statistically inconclusive effect on economic growth.

Furthermore, considering that enhanced financialization and higher income inequality are features of liberal market economies (LMEs) in varieties of capitalism (VoC) literatures (Lazonick, 2010; Lee and Shin, 2021), this study additionally analyzed the effect of radical innovation on equity, which is another feature of LMEs (Hall and Soskice, 2001) and often measured by the qualitative aspects or generality of patents. Then, this study finds that the radicality of innovation does not significantly or robustly affect aggravating inequality, which indicates that higher income inequality of LMEs is primarily due to its financialization features rather than radical innovation.

In country-level equity (and growth) studies, the key contributions of this study are as follows: First, in methodological aspects, this study proposes country panel recursive VAR model for income inequality (and economic growth) that can not only address the drawbacks of conventional cross-sectional country panel analysis but also enables to compare the impacts of various equity (or growth) determinants in a single empirical framework. Second, in application, this study finds no statistically significant evidence of technological innovation aggravating income inequality, which differs from Aghion et al. (2018) utilizing conventional cross-sectional panel analysis.

The remainder of this paper is organized as follows. Section 2 reviews literatures on the equity impacts of financialization and technological innovation and discusses related research gaps which this study focuses on. Section 3 discusses empirical approach, model specification, and datasets utilized by this study. Section 4 presents the empirical findings and discusses related implications. Last, Section 5 concludes the paper.

2. Literature Review

2.1. Equity Impact of Technological Innovation

Regarding the distributional impact of technological innovation, several labor economists argued that technological innovation negatively affects low-skill employment and thus aggravates income inequality. For instance, using household-level data, the literatures of *skill-biased technological change* (SBTC) unveiled that the skill premium—the wage ratio between college and non-college workers—has increased since the 1980s. On the basis of such observation, they concluded that it is caused by technological changes that lead to the increasing demand on college workers; especially, the speed of increasing demand is faster than that of the increasing supply of skilled labor (Katz and Autor, 1999; Katz and Goldin, 2008; Katz and Murphy, 1992). The detailed explanation for the

finding is that the introduction of automation and computers replaces routine occupations (Acemoglu and Autor, 2011; Autor et al., 1998, 2002, 2003, 2008).[1] Similarly, also based on household-level data, several scholars argued that middle-wage occupations are replaced by high- and low-wage ones, which is referred to as job polarization (Goos et al., 2009, 2014; Goos and Manning, 2007). In addition to SBTC literatures based on *household-level* micro data, several recent studies that utilized *firm-level* micro data provided similar implications. For instance, using Swiss firm-level digitalization and innovation data, Balsmeier and Woerter (2019) argued that digitalization replaces low- and medium-skill employees with high-skilled labor. Moreover, focusing on service sectors, Evangelista and Savona (2003) uncovered that high-skilled employment replaces low-skilled one, which is related to information and communication technologies (ICTs).

Despite that SBTC and related literatures discussed how the advancement of computer or digital technologies affects income inequality, those studies have several critiques and drawbacks. First, Card and DiNardo (2002) argued that the wage inequality between skilled- and unskilled-labor "stabilized in the 1990s despite continuing advances in computer technology." Moreover, those studies have a certain limitation that they cannot discuss the equity impact of technological innovation other than the ones related to computer technology, and the innovation of other sectors may have a different effect. For instance, Lee and Clarke (2019) suggested that the innovation of overall high-tech sectors impacts employment differently depending on its job qualifications, such as low-, mid-, and high-skilled jobs. Specifically, using the data of United Kingdom, they uncovered that the employment growth of tradable high-tech industries, not only including the digital economy but also STEM-intensive sectors, affects non-tradable mid- and low-skilled workers differently. On the basis of the jobs multiplier model of Moretti (2010), they argued that low-skilled workers benefit from the increased employment rate through the growth of high-tech sectors but suffer from lower average wages especially when increased housing cost is considered. Meanwhile, they unveiled that mid-skilled workers gain from higher wages without the change in the employment rate. Given that innovation is generally derived by high-tech sectors, such complex role of innovation in low- and mid-skilled labor makes it inconclusive whether innovation aggravates or mitigates income inequality.

In addition to the studies focusing on micro-level data, there also exist macroeconomic literatures that directly discussed the impact of innovation on aggregate-level inequality rather than through labor employment. Jones and Kim (2018) theoretically discussed the effect of innovation on top income share by applying the Schumpeterian growth model. Based on their contribution, using

[1] The impact on routine occupations is also referred to as routine-biased technological change (RBTC) (Goos et al., 2014).

measures on the basis of patent data, Aghion et al. (2018) empirically analyzed the inequality effect of innovation and introduces the Schumpeterian macroeconomic model. Their argument is based on the perception that innovation increases monopolistic rents of incumbents, and the monopolist profit serves as the source of income inequality in the shape of Pareto distribution. Accordingly, Aghion et al. (2018) measured innovation in terms of (quality-adjusted) patent size, given that patent preserves the profits of incumbent entrepreneurs, and they empirically found that innovation increases top income shares.

2.2. Role of Financialization in Income Inequality

On the basis of the conventional notion that capital income is primarily an income source of the rich, whereas the poor relatively rely more on labor income (Kaldor, 1955), the factors related to financial sector have been considered determinants of income inequality.

One traditional aspect of the financial sector related to equity study is financial development. Levine (2005) defined financial development as "improvements in the (i) production of ex ante information about possible investments, (ii) monitoring of investments and implementation of corporate governance, (iii) trading, diversification, and management of risk, (iv) mobilization and pooling of savings, and (v) exchange of goods and services." Although financial development is generally found to accelerate economic growth (e.g., Beck and Levine (2004), King and Levine (1993), and Levine and Zervos (1998), and so on), there exist mixed arguments regarding the impact of financial development on income inequality. For instance, Greenwood and Jovanovic (1990) argued that the equity effect of financial development is non-linear and similar to Kuznets' (1955) inversed-U hypothesis; financial development aggravates income inequality at the early stages of economic development then mitigates it later. Meanwhile, Beck et al. (2007) and Clarke et al. (2003) uncovered that financial development decreases income inequality. The theoretical argument of financial development aggravates income inequality is based on that "it relaxes credit constraints that more extensively restrain the poor," whereas the opposite assertion focuses on that the rich have relatively higher accessibility to the financial market (Beck et al., 2007).

In addition to financial development, recent literatures focused on the impact of *financialization* on income inequality. The studies on financialization have recently received attention because of the case of United States and the global financial crisis in 2008 (Tomaskovic-Devey and Lin, 2011). The foremost difference between financial development and financialization is that the former generally indicates the development of financial institution related to its intermediary functions, whereas the latter is closely related to the increasing influence of financial activities on

non-financial firms. Specifically, Kus (2012) defined financialization as "(1) the growing share of the financial sector in the economy, (2) the growing reliance of non-financial firms' on financial activities as a source of revenue, (3) the emergence of a new corporate governance view that sees the firm as a bundle of tradable assets, and (4) the increasing of household engagement with financial markets as consumers of credit or as purchasers of investment products, seeking to generate income or sustain living standards."

Although first observed in in United States, financialization is now a common phenomenon in advanced countries (Kus, 2012). Moreover, studies on financialization generally argued that higher financialization not only reduces the economic growth of non-financial sectors (Tomaskovic-Devey et al., 2015) but also increases income inequality (Kus, 2012; Lin and Tomaskovic-Devey, 2013; Tomaskovic-Devey and Lin, 2011). The key mechanism of financialization aggravating income inequality is that it results in the decrease of the wages for non-financial sector employees. Specifically, the expansion of the financial sector decreases the profitability of non-financial sectors, and a new corporate governance emphasizing shareholders' interest compels managers to focus on short-run profits and cut labor costs (Kus, 2012). Furthermore, the increasing reliance of non-profit sectors on financial income reallocates resources from workers and fixed capital investments to financial markets (Lin and Tomaskovic-Devey, 2013).

In country-level empirical analysis, using data of OECD countries Kus (2012) found that financialization measured by the value of stock traded and pre-tax bank income as a percent of GDP and securities under bank assets aggravate income inequality measured through the Gini index. In addition, Alexiou et al. (2021) provided similar findings on OECD countries, however, they found that the distributional impact of financialization is complex depending on its measures. Moreover, Kwon and Roberts (2015) argued that financialization enhances other factors increasing income inequality, and Dünhaupt (2016) asserted that financialization is a cause of recent declining labor income share.

2.3. Discussion on Research Gaps

Despite extensive empirical analyses on the distributional impact of innovation or financialization, those studies have several common drawbacks that must be addressed and research gaps, which this study focuses. The key limitation of those studies is that they utilized *cross-sectional panel* approaches, which is basically an application of cross-sectional estimation to panel data. For instance, Aghion et al. (2018) introduced fixed-effect estimation with an instrument, and Kus (2012) adopted dynamic panel GMM estimation. In addition, the analyses of Kwon and Roberts (2015), Dünhaupt

(2016), and Alexiou et al. (2021) utilized fixed effects model with Paris–Winsten, feasible GLS, and Driscoll and Karry's (1998) nonparametric covariance matrix, respectively.

In a cross-sectional (panel) analysis, the effect of each regressor is interpretated under the condition of *ceteris paribus*; the condition that other regressors are fixed. Accordingly, a cross-sectional (panel) approach does not consider feedback effects among variables, especially the ones between regressors; the impact of a dependent variable on regressors is often addressed through endogeneity control. However, variables in a country-level analysis are generally endogenous themselves (Durlauf, 2009), and possible feedback effects among the regressors must be considered. Moreover, based on the condition, the regressors, other than the variables(s) of interest function as control factors, which are often chosen without solid theoretical basis whether a certain control factor is to be included in the model or not. For instance, despite utilizing similar dependent variables, such as Gini coefficient or top income shares, various equity literatures seem to choose different control variable sets depending on their equity determinants of interest and/or data availability. Accordingly, such differences also complicate comparing the equity impact of various factors discussed by different literatures.

To address these drawbacks, this study introduces *panel time-series* approaches, which is based on time-series perspectives, instead of cross-sectional framework. Specifically, this study utilizes panel structural VAR model with recursive identification, which will be discussed with details in the following section. The recursive VAR model has certain advantages that it not only allows feedback effects among regressors but also considers regressor variables other than those of interest as transmission mechanisms rather than controls. By specifying the transmission mechanism to be parsimonious with clear theoretical basis, this study introduces a panel time-series model for income inequality which can compare equity effects of various determinants in a single framework and address issues of cross-sectional panel analysis on country-level data.

3. Empirical Strategies

3.1. Panel Time-Series and Local Projections Approach

In analyzing the impact of technological innovation and financialization on income inequality, this study introduces panel structural VAR model on the basis of panel time-series perspective. [2]

[2] Panel time-series approach is also called a large heterogenous panel, because the time dimension of panel time-series data is relatively larger (i.e., large-T) than the ones of cross-sectional panel, and the approach generally assumes coefficients (slops) to be heterogenous across panel units (Pesaran, 2015b).

Conventional cross-sectional panel analysis perceives panel data as cross-sectional one with multiple time observations, and its estimation approaches are basically rooted in cross-sectional ones (e.g., a method of using instruments to address endogeneity issue, and so on). Then, cross-sectional panel approach additionally considers issues related to multiple time observations (e.g., fixed- or random-effect model to control time-invariant panel-specific effects, and dynamic panel GMM estimation for the model with lagged dependent variables as a regressor, and so on). Meanwhile, panel time-series analysis considers panel data as time-series data of multiple panel units, and its empirical approaches are accordingly based on time-series methods (e.g., unit-root, cointegration test, and so on). Although early studies of country panel analysis are generally based on cross-sectional panel approaches (e.g., Islam (1995), Barro (2000), and so on), recent studies begin to adopt panel time-series analysis (e.g., Chudik et al. (2017), and so on), so that time (yearly) observations are accumulated enough to conduct time-series-based approaches.

In a country panel data analysis, an important advantage of panel time-series analysis compared to cross-sectional panel one is that it can address various drawbacks in utilizing cross-sectional panel approach with country-level data. Despite the necessity of analyzing country panel data in several research strands, such as economic development (growth) and income inequality, there have been several critiques of cross-sectional panel analysis. Particularly, Durlauf (2009) summarized the critiques regarding empirical analyses on economic growth (i.e., *growth regression*), which are also applicable to other research topics using similar country-level cross-sectional panel analysis, such as income inequality. Despite that addressing those critiques in cross-sectional panel framework have been difficult, by adopting time-series approaches, panel time-series approach can address them as follows:

First, regarding the *endogeneity* that the regressors are themselves endogenous, and thus the discussion on causality is invalid (Durlauf, 2009), the critique can be addressed by introducing structural VAR model and identifying structural shocks which are exogenous and orthogonal to each other. VAR analysis considers all variables to be endogenous by allowing feedback effects among variables; not only the effects of dependent variables on regressors but also the effects between regressors. Furthermore, with properly specifying shock structure and related restrictions, introducing structural VAR enables to identify structural shocks and facilitates the discussion on causal effects.

Moreover, the *model uncertainty* issue related to arbitrary choice of control variables, which is also discussed by the sensitivity analysis of Levine and Renelt (1992), can be addressed through the econometrical interpretations in panel structural VAR analysis with recursive identification, which differ from the ones in the cross-sectional analysis. In terms of a cross-sectional panel approach, the interpretation on the effects of regressors is based on *ceteris paribus*; the interpretation of one

regressor is under the condition of holding other regressors constant. Accordingly, choosing a regressor set can greatly affect the estimation results and is inevitably susceptible to arbitrary selection unless there exist definite reasons for each variable to be included in or excluded from the model. Meanwhile, the regressors in a panel structural VAR model with recursive identification are indicative of the *transmission mechanis*m for the dependent variables. Thus, the regressor set can be free from the ad-hoc selection issue when the model specification has a solid theoretical basis.

Finally, in response to the *exchangeability* issue that heterogeneity across countries must be considered, panel time-series approach explicitly allows heterogenous slopes (coefficients) across panel units. The foremost difference between panel time-series and cross-sectional approach in panel heterogeneity is that the former assumes all coefficients, slope and intercept terms, to be heterogenous, whereas the latter considers the heterogeneity only in constant terms (e.g., fixed-effect model). As Pesaran and Smith (1995) argued that dynamic panel model, including lagged dependent variable as a regressor, should explicitly assume heterogenous slopes to acquire consistent estimates, following panel time-series literatures with frequentist perspectives[3] generally considers parameters to be heterogenous unless assuming parameter homogeneity is also found to yield consistent estimators. Moreover, by specifying transmission mechanism variables for the structural VAR model as the ones commonly applicable to most countries, panel time-series approach can also address an additional critique of Durlauf (2009) that country heterogeneity, not only in parameters but also in model specification, must be considered.

Regarding the estimation method, this study adopts common correlated effect mean-group (CCEMG) estimator proposed by Pesaran (2006). One advantage of CCEME estimator is that it is asymptotically unbiased as not only $N, T \to \infty$ but also $N \to \infty$ with fixed T (Pesaran, 2006), which is particularly useful for country-level analysis when the time dimension is not large enough. In econometrical aspects, CCEMG estimator considers following two issues commonly discussed in panel time-series literatures:

First, regarding panel heterogeneity, CCEMG estimator introduces *mean-group* (MG) method, which first individually estimates parameters across panel units, then calculates their average value. MG estimator is first proposed by Pesaran and Smith (1995), and the approach has been adopted by numerous panel time-series estimators. As an example, MG estimator can be presented as follows:

$$\hat{\beta}_{MG} = N^{-1}\sum_{i=1}^{N}\hat{\beta}_i. \quad (1)$$

[3] In Bayesian estimation, heterogeneity across panel units can be considered through parameters that are assumed to be random variables.

The other econometrical issue to be discussed is *cross-sectional dependency* (CD) related to *common correlated effect* (CCE) in error terms, which can be presented as follows:

$$u_{it} = \boldsymbol{\gamma_i}\mathbf{f_t} + \varepsilon_{it}. \tag{2}$$

Ultimately, CCE indicates unobserved common cross-sectional factors correlated across panel units ($\mathbf{f_t}$), but heterogenous in their effect on each panel units ($\boldsymbol{\gamma_i}$). CCE seems to be an analogy of time fixed effect in a cross-sectional panel analysis. However, although time fixed effect assumes the size of common effect to be homogenous across panel units, CCE allows heterogeneity in the size of common factor effects. Cross-sectional panel and early panel time-series methods generally assume cross-sectional independency, but recent large heterogenous panel estimators consider cross-sectional dependency and slope heterogeneity, given that ignoring cross-sectional dependency yields serious biasness (Pesaran, 2006).

In panel time-series literatures, cross-sectional dependency is often controlled by augmenting the model with cross-sectional means of dependent or regressor variables (e.g., Pesaran (2006) and Chudik and Pesaran, (2015), and so on.), which is also referred to as *cross-sectional (CS) augmentation* (Chudik et al., 2016, 2017). The approach can be presented by an example as

$$u_{it} = \phi'_{ij}\bar{\mathbf{v}}_{t-j} + \varepsilon_{it}, \tag{3}$$

where $\bar{\mathbf{v}}_{t-j}$ is a vector for cross-sectional means of CS augmentation variables. In terms of the CCEMG estimator, the model is augmented with cross-sectional means of dependent variable and regressors.

Regarding the (panel) time-series analysis on (structural) VAR model, the impact of one variable on another is generally discussed by deriving impulse response function (IRF). Meanwhile, IRF is conventionally derived by bootstrapping with maximum-likelihood (ML) estimation or Markov-chain Monte-Carlo (MCMC) simulation with Bayesian estimation, which require significant amounts of computation, several recent studies alternatively adopted the LP method proposed by Jordà (2005). LP is a concise method of deriving IRF that neither estimating the underlying VAR model nor complicated computation procedures is necessary. First proposed by Jordà (2005), LP approach has been widely adopted by various econometric literatures, such as Auerbach and Gorodnichenko (2016) and Ramey and Zubairy (2018), and so on. Moreover, Plagborg-Møller and

Wolf (2021) econometrically proved that LP and structural VAR estimates have the same impulse responses, which provides theoretical basis of utilizing LP analysis as an alternative of structural VAR estimation.

The foremost advantage of LP approach in analyzing country panel data is that LP enables to estimate IRF with conventional econometrical approaches (Jordà, 2005). Accordingly, existing and well-established panel time-series estimators can be directly applied to estimate LP specifications, without any additional considerations on econometrical issue. Regarding LP analysis on income inequality, there have been several literatures that analyzed country panel data with LP approach (Ball et al., 2011, 2013; Furceri et al., 2017, 2018; Furceri and Loungani, 2018; Ostry et al., 2019). However, econometrical approaches of those literatures are based on cross-sectional panel analysis instead of panel time-series one: They simply adopted the LP specifications without considering the panel time-series features. Meanwhile, the LP analysis of this study introduces panel time-series approaches which carefully considers time-series properties in using country panel data.

3.2. Model Strategy

This study derives a panel time-series model for income inequality by referring empirical models of economic growth. The underlying intuition of such approach is that economic growth and income inequality are commonly related to the dynamics of income distribution. Specifically, income inequality studies are interested in detailed features of income distribution, and studies on economic growth focus on the average (i.e., per capita) income of the whole population. Moreover, recent income inequality studies focused on top income shares rather than aggregate measures, such as Gini coefficient, given that top income shares directly indicate income discrepancy between the rich and the poor and thus can provide more intuitive understandings (Piketty, 2014). In such case, log of top $x\%$ income share indicates the log-difference in per capita income between top $x\%$ and entire population group (minus a constant, $\log(100/x)$). Accordingly, linear regression analysis on economic growth with log of per capita income is applicable to income inequality analysis, and the impact of equity determinants estimated through the analysis can be interpreted as the difference in per capita income effect between the rich and entire population. In addition, the approach of utilizing economic growth model and top income shares has been utilized by Jones and Kim (2018) and Aghion et al. (2018) which derived the income inequality model from the growth model of Schumpeterian perspectives.

Specifically, deriving a panel time-series model for income inequality from the empirical model of economic growth is conducted as follows. First, this study derives a dynamic country panel

model for (log of) average per capita income by referring to an empirical model of neoclassical growth theory proposed by Mankiw et al. (1992) and Islam (1995), growth accounting literatures, such as Caselli (2005) and Hall and Jones (1999), and stylized facts discussed by Kaldor (1957). Then, applying panel time-series perspectives, this study rewrites the model in the form of VAR model with recursive identification to which LP approach is applicable. Finally, this study expands the structural VAR (and related local projection) model for average per capita income to the one for income inequality measured by log of top income shares.

In deriving the dynamic panel model for income dynamics, this study adopts the approach proposed by Mankiw et al. (1992) and Islam (1995). However, on the basis of growth accounting studies (Caselli, 2005; Hall and Jones, 1999) and Kaldor's (1957) finding, this study introduces an alternative production function with labor-augmenting productivity measured as Solow's residual. Although applied to numerous empirical analysis (e.g., Berg et al. (2018)), the model of Mankiw et al. (1992) and Islam (1995) are fundamental to discussing the role of convergence (initial income level) in the framework of endogenous growth theory focusing on human capital, and thus their model has several drawbacks in discussing determinants of income dynamics, especially with panel-time series approach: First, the production function of Mankiw et al. (1992) and Islam (1995) calibrated the growth rate of labor-augmenting productivity as a constant of 0.02, which accordingly implies that the change in per capita income is fully accounted by initial income level, investment on physical capital, and that on human capital investment (measured by education factor). However, growth accounting studies, such as Caselli (2005) and Hall and Jones (1999) found that, even considering the role of education, economic growth cannot be fully explained through capital investments. Furthermore, education datasets generally provide variables with gaps rather than with yearly basis, which are inappropriate to be utilized in panel time-series analysis. For instance, the dataset of Barro and Lee (2013) has 5-year gaps, that of Cohen and Soto (2007) has 10-year gaps, and that of UNESCO has irregular gaps. Thus, to address the drawbacks, this study introduces labor-augmenting productivity measured by Solow's residual. Although growth accounting studies proposed total factor productivity (TFP) to measure the portion of economic growth not accounted by factor inputs, this study introduces productivity in the form of labor-augmentation, which is consistent with Kaldor's (1957) stylized facts.

As a result of the discussion, this study considers a production function of constant returns to scale (CRS) and law of motion for physical capital as follows:

$$Y(t) = K(t)^{\alpha}\big(z(t)N(t)\big)^{1-\alpha}, \tag{4}$$

$$\text{and } \dot{K}(t) = s \cdot Y(t) - \delta \cdot K(t), \tag{5}$$

where $Y(t)$ and $K(t)$ are aggregate income and capital stock, respectively, $z(t)$ is labor-augmenting productivity, $N(t)$ is population, α is share of capital compensation to aggregate income (i.e., capital income share), s is investment (gross fixed capital formation) ratio to aggregate income, and δ is depreciation rate of physical capital. Rewriting Equations (4) and (5) in the form of per capita unit yields the following equations:

$$y(t) = z(t)^{1-\alpha} k(t)^{\alpha}, \tag{6}$$

$$\text{and } \dot{k}(t) = s \cdot y(t) - (n + \delta)k(t), \tag{7}$$

where $y(t) \equiv Y(t)/N(t)$, $k(t) \equiv K(t)/N(t)$, and n is population growth rate. Given the labor-augmenting productivity level, $z(t)$, steady state levels of capital and output per capita, k^* and y^* respectively, can be presented as follows:

$$k^* = z(t) \cdot [s/(n + \delta)]^{1/(1-\alpha)}, \tag{8}$$

$$\text{and } y^* = z(t) \cdot [s/(n + \delta)]^{\alpha/(1-\alpha)}. \tag{9}$$

Approximating around steady state yields the following differential equation:

$$\partial \log y(t)/\partial t = \lambda[\log y^* - \log y(t)] + \eta \cdot g_z(t), \tag{10}$$

where $\lambda = (1 - \alpha)(n + \delta)$, $\eta = 1 - \alpha$ and $g_z(t) = \dot{z}(t)/z(t) = \partial \log z(t)/\partial t$. Solving the differential equation with defining the initial period as t_0 yields

$$\log y(t) = \left(1 - e^{-\lambda\tau}\right) \log y^* + e^{-\lambda\tau} \log y(t_0) - \eta \cdot \left[\chi(t) - e^{-\lambda\tau}\chi(t_0)\right], \tag{11}$$

where $\tau = t - t_0$, and $\chi(t) = \sum_{j=1}^{\infty}(-\lambda^{-1})^j \left[\partial^j \log z(t)/\partial t^j\right]$. Setting the initial period as $t_0 = t - 1$, applying discrete time framework with the approximation of $\partial \log z(t)/\partial t \approx \log z(t) - \log z(t-1)$, and substituting steady state per capita output with (8) yield the following empirical model:

$$\log y_t = \rho \log y_{t-1} + \beta_0 \log x_t + \sum_{j=0}^{\infty} \gamma_j \log z_{t-j} + \varepsilon_t, \quad (12)$$

where $x_t = s_t/(n_t + \delta_t)$. Then, the Equation (12) can be extended to a country panel model allowing heterogenous coefficients and unobserved panel unit specific effect as follows:

$$\log y_{it} = c_{y,i} + \rho_i \log y_{i(t-1)} + \beta_{i0} \log x_{it} + \sum_{j=0}^{\infty} \gamma_{ij} \log z_{i(t-j)} + \varepsilon_{it}. \quad (13)$$

From the heterogenous panel growth model above, this study derives a structural VAR model with recursive identification for income inequality. First, in expanding the growth model to (reduced form) VAR specification, this study allows the steady state effect of lagged capital investment factors, which additionally includes $x_{i(t-j)}$ $(j = 1, 2, ...)$ as follows:

$$\log y_{it} = c_{y,i} + \rho_i \log y_{i(t-1)} + \sum_{j=0}^{\infty} \beta_{ij} \log x_{i(t-j)} + \sum_{j=0}^{\infty} \gamma_{ij} \log z_{i(t-j)} + \varepsilon_{y,it}. \quad (14)$$

Regarding the model specification, the lag order of the dependent variable should be fixed to one, because the model is originally derived by solving the differential equation of the neoclassical growth model, and the initial period is set to $t - 1$. Meanwhile, utilizing current period variables as steady state proxies is merely based on the standard partial adjustment approach that considers the target (optimal) value of dependent variable to be determined by the explanatory variables of the current period (Islam, 1995). Therefore, by simply considering the *possible* lagged effect on steady state, the lag order of investment-related factor can be extended. This study sets the lag order of capital investment factor as infinite to allow feedback effects between labor augmenting productivity whose lag is set to infinite. Then, as a reverse approach of Chudik et al. (2016), which derives an ARDL model from a VAR specification, Equation (14) can be considered a derivation from the following reduced-form VAR model:

$$\begin{bmatrix} \log z_{it} \\ \log x_{it} \\ \log y_{it} \end{bmatrix} = \begin{bmatrix} c_{z,i} \\ c_{x,i} \\ c_{y,i} \end{bmatrix} + \sum_{j=1}^{\infty} B_{ij} \begin{bmatrix} \log z_{i(t-j)} \\ \log x_{i(t-j)} \\ \log y_{i(t-j)} \end{bmatrix} + \begin{bmatrix} u_{z,it} \\ u_{x,it} \\ u_{y,it} \end{bmatrix}, \quad (15)$$

where $B_{ij} = \begin{bmatrix} b_{zz,ij} & b_{zx,ij} & b_{zy,ij} \\ b_{xz,ij} & b_{xx,ij} & b_{xy,ij} \\ b_{yz,ij} & b_{yx,ij} & b_{yy,ij} \end{bmatrix}$, $b_{zy,ij} = b_{xy,ij} = b_{yy,ij} = 0$ for $j > 1$,

$$u_{y,it} = \omega_i' \begin{bmatrix} u_{z,it} \\ u_{x,it} \end{bmatrix} + \varepsilon_{y,it},$$

$$\text{and } \omega_i \equiv \begin{bmatrix}\gamma_{i0}\\ \beta_{i0}\end{bmatrix} = E\begin{bmatrix}u_{z,it}u_{z,it} & u_{z,it}u_{x,it}\\ u_{x,it}u_{z,it} & u_{x,it}u_{x,it}\end{bmatrix}^{-1} E\begin{bmatrix}u_{z,it}u_{y,it}\\ u_{x,it}u_{y,it}\end{bmatrix}.$$

Then, this study introduces recursively ordered shock structure to analyze the impact of other factors on per capita income with following considerations. First, in neoclassical growth theory, the exogenous increase in productivity reflecting technological progress is the source of economic growth, and the investment on physical capital responses to the productivity growth. Thus, the productivity shock is to be prior to the investment shock. Moreover, considering the implications of Barro's *conditional convergence* model (Barro, 1991; Barro and Sala-i-Martin, 1992) that various institutional factors affect income level through capital investment, the investment shock is to be placed right before the per capita income shock. In addition, when the productivity factor is supposed to be *Solow's residual*, the dynamics of per capita income are fully accounted by productivity and investment factor, and thus they function as a *transmission mechanism*; that is, any other per capita income effect is through productivity and/or capital investment.

Resultantly, the impact of a third factor on per capita income dynamics can be analyzed in the recursive VAR model by ordering its shock before productivity shock or between productivity and investment shock. In case that the shock of a third factor, w_{it}, is determined prior to productivity, for instance, the recursive VAR model can be presented as follows:

$$\begin{bmatrix} w_{it}\\ \log z_{it}\\ \log x_{it}\\ \log y_{it}\end{bmatrix} = \begin{bmatrix} c_{w,i}\\ c_{z,i}\\ c_{x,i}\\ c_{y,i}\end{bmatrix} + \sum_{j=1}^{\infty} B_{ij}\begin{bmatrix} w_{i(t-j)}\\ \log z_{i(t-j)}\\ \log x_{i(t-j)}\\ \log y_{i(t-j)}\end{bmatrix} + \begin{bmatrix} u_{w,it}\\ u_{z,it}\\ u_{x,it}\\ u_{y,it}\end{bmatrix}, \tag{16}$$

$$\text{where } \begin{bmatrix} u_{w,it}\\ u_{z,it}\\ u_{x,it}\\ u_{y,it}\end{bmatrix} = A_i\begin{bmatrix} \varepsilon_{w,it}\\ \varepsilon_{z,it}\\ \varepsilon_{x,it}\\ \varepsilon_{y,it}\end{bmatrix},$$

and A_i is a lower triangular matrix for recursive ordering structure.

Fundamentally, the third factor shock identified by the model is orthogonal to any other factor reflected in the other shocks. Specifically, the estimated impact of the third factor is the effect not explained by the other factors through productivity and/or capital investment. Therefore, given that productivity and capital investment are the *least common* determinants of per capita income dynamics, the model specification is free from the critiques related to arbitrary selection of control variables or possible heterogeneity in model specification, which were discussed by Durlauf (2009).

On the basis of the recursive VAR model for average per capita income, this study derives the model for income inequality measured by top income shears focusing on the intuition that the effects on per capita income can be heterogenous across groups with different income levels, which can be presented as

$$\begin{bmatrix} w_{it} \\ \log z_{it} \\ \log x_{it} \\ \log y(p)_{it} \end{bmatrix} = \begin{bmatrix} c(p)_{w,i} \\ c(p)_{z,i} \\ c(p)_{x,i} \\ c(p)_{y,i} \end{bmatrix} + \sum_{j=1}^{\infty} B(p)_{ij} \begin{bmatrix} w_{i(t-j)} \\ \log z_{i(t-j)} \\ \log x_{i(t-j)} \\ \log y(p)_{i(t-j)} \end{bmatrix} + A(p)_i \begin{bmatrix} \varepsilon_{w,it} \\ \varepsilon_{z,it} \\ \varepsilon_{x,it} \\ \varepsilon_{y(p),it} \end{bmatrix}, \quad (17)$$

where $y(p)_{it}$ indicates per capita income of top p% income group. Moreover, when income inequality is measured by log of top p% income share, $q(p)_{it}$, it can be presented as the difference between logged per capita income among different population groups as follows:

$$\log q(p)_{it} \equiv \log(Y(p)_{it}/Y(100)_{it}) = \log \tilde{q}(p)_{it} - \varphi(p), \quad (18)$$

where $\log \tilde{q}(p)_{it} \equiv \log y(p)_{it} - \log y(100)_{it}$, $\varphi(p) \equiv \log(100/p)$, and $Y(p)_{it}$ is aggregate income of top p% population. Then, by taking the difference of Equation (17) between top p% and entire (top 100%) population, this study derives the following income inequality model:

$$\begin{bmatrix} w_{it} \\ \log z_{it} \\ \log x_{it} \\ \log \tilde{q}(p)_{it} \end{bmatrix} = \begin{bmatrix} \tilde{c}(p)_{w,i} \\ \tilde{c}(p)_{z,i} \\ \tilde{c}(p)_{x,i} \\ \tilde{c}(p)_{\tilde{q},i} \end{bmatrix} + \sum_{j=1}^{\infty} \tilde{B}(p)_{ij} \begin{bmatrix} w_{i(t-j)} \\ \log z_{i(t-j)} \\ \log x_{i(t-j)} \\ \log \tilde{q}(p)_{i(t-j)} \end{bmatrix} + \tilde{A}(p)_i \begin{bmatrix} \varepsilon_{w,it} \\ \varepsilon_{z,it} \\ \varepsilon_{x,it} \\ \varepsilon_{\tilde{q}(p),it} \end{bmatrix}, \quad (19)$$

where $\tilde{c}(p)_{\cdot,i} = c(p)_{\cdot,i} - c(100)_{\cdot,i}$ $\tilde{B}(p)_{ij} = B(p)_{ij} - B(100)_{ij}$, and $\tilde{A}(p)_i = A(p)_i - A(100)_i$. Then, as $\Delta \log \tilde{q}(p)_{it} = \Delta \log q(p)_{it}$, by first-differencing the model in consideration of (possible) unit-roots in variables, following panel recursive VAR model for top income shares can be derived as

$$\begin{bmatrix} \Delta w_{it} \\ \Delta \log z_{it} \\ \Delta \log x_{it} \\ \Delta \log q(p)_{it} \end{bmatrix} = \sum_{j=1}^{\infty} \tilde{B}(p)_{ij} \begin{bmatrix} \Delta w_{i(t-j)} \\ \Delta \log z_{i(t-j)} \\ \Delta \log x_{i(t-j)} \\ \Delta \log q(p)_{i(t-j)} \end{bmatrix} + \tilde{A}(p)_i \begin{bmatrix} \Delta\varepsilon_{w,it} \\ \Delta\varepsilon_{z,it} \\ \Delta\varepsilon_{x,it} \\ \Delta\varepsilon_{q(p),it} \end{bmatrix}. \quad (20)$$

Using the equation for the dependent variable of a recursive VAR model, an impulse response

of one (dependent) variable to the structural shock of another (explanatory) variable can be analyzed through the LP approach by additionally including current values of the variable of interest and other variables whose shocks are determined prior to the shock of interest (Plagborg-Møller and Wolf, 2021). In case of the model presented by the Equation (20), for instance, the impulse response of $\Delta \log q(p)$ to the structural shock of Δw, a third factor, can be analyzed by the following specification:

$$\begin{aligned}\Delta \log q(p)_{i(t+s)} = {} & \sum_{j=0}^{\infty} \tilde{b}_{ij,yw}^{(s)} \Delta w_{i(t-j)} + \sum_{j=1}^{\infty} \tilde{b}_{ij,yz}^{(s)} \Delta \log z_{i(t-j)} \\ & + \sum_{j=1}^{\infty} \tilde{b}_{ij,yx}^{(s)} \Delta \log x_{i(t-j)} + \tilde{b}_{i1,yy}^{(s)} \Delta \log q(p)_{i(t-1)} + e_{q(p),it}^{(s)},\end{aligned} \tag{21}$$

where $\tilde{b}_{0,yw}^{(s)}$ presents the impulse response of $\Delta \log q(p)_{t+s}$ to the structural shock on Δw. In addition, the cumulative impulse response can be specified as follows:

$$\begin{aligned}\Delta \log q(p)_{it}^{(h)} = {} & \sum_{j=0}^{\infty} \tilde{b}_{ij,yw}^{(h)} \Delta w_{i(t-j)} + \sum_{j=1}^{\infty} \tilde{b}_{ij,yz}^{(h)} \Delta \log z_{i(t-j)} \\ & + \sum_{j=1}^{\infty} \tilde{b}_{ij,yx}^{(h)} \Delta \log x_{i(t-j)} + \tilde{b}_{i1,yy}^{(h)} \Delta \log q(p)_{i(t-1)} + e_{q(p),it}^{(h)},\end{aligned} \tag{22}$$

where $\Delta \log q(p)_{it}^{(h)} = \log q(p)_{i(t+h)} - \log q(p)_{i(t-1)}$, and $\tilde{b}_{i0,yw}^{(h)} = \sum_{s=0}^{h} \tilde{b}_{i0,yw}^{(s)}$, which indicates the cumulative impulse responses. As the first-differenced model is estimated, and the primary interest lies in the level value rather than the differenced one, this study focuses on cumulative impulse responses.

Finally, this study applies panel time-series estimation to the LP specification with considering slope heterogeneity and cross-sectional dependency as follows: Regarding the former, this study introduces MG estimation referring to other panel time-series analyses, which can be presented as

$$\hat{\tilde{b}}_{MG,yw}^{(h)} = N^{-1} \sum_{i=1}^{N} \hat{\tilde{b}}_{i0,yw}^{(h)}. \tag{23}$$

In response to the latter, this study augments the model with cross-sectional means of the dependent variables and current value(s) of the variable(s) included in the model; the variables related to the shock of interest and predetermined ones. The reason is because the error term of LP model represents *exogenous* shocks of current period and related responses. Moreover, regarding the lag order specification, this study approximates the infinite lag order with $J = \left[T_{\max}^{1/3}\right]$ referring to the literatures of Chudik and Pesaran (2015) and Chudik et al. (2016, 2017), which is mostly three in the

case of this study. Resultantly, Equation (23) is modified as the following specification estimated by this study:2

$$\begin{aligned}\Delta \log q(p)_{it}^{(h)} = & \sum_{j=0}^{J} \tilde{b}_{ij,yw}^{(h)} \Delta w_{i(t-j)} + \sum_{j=1}^{J} \tilde{b}_{ij,yz}^{(h)} \Delta \log z_{i(t-j)} \\ & + \sum_{j=1}^{J} \tilde{b}_{ij,yx}^{(h)} \Delta \log x_{i(t-j)} + \tilde{b}_{i1,yy}^{(h)} \Delta \log q(p)_{i(t-1)} \\ & + \overline{\Delta \log q(p)^{(h)}}_{t} + \overline{\Delta w}_{t} + \tilde{e}_{q(p),it}^{(h)}.\end{aligned} \tag{24}$$

3.3. Data and Variables

The country-level panel sample of this study comprises 24 countries with yearly observations from 1976 to 2017: Australia, Brazil, Canada, China, Germany, Spain, Finland, France, United Kingdom, Greece, Hungary, India, Italy, Japan, Republic of Korea, Mexico, Norway, New Zealand, Philippines, Poland, Singapore, Sweden, United States, and South Africa. The country covers most regions except Middle East and North Africa. Including various countries is important for panel time-series analysis to control common correlated effects through cross-sectional averages. Regarding the time span, the initial sample period is set to 1976, for United States patents bulk data provides full citation information since 1976, and the last period is set to 2017 because of the availability of financialization measures. In addition, the time horizon for impulse response analysis is set to eight years (i.e., total of nine years, including the initial period), which can analyze impulse responses over 30 quarters after the initial shock.

This study utilizes log of top 1% and 5% income shares (to aggregate income) as measures of income inequality which are provided by the World Inequality Database (hereafter WID). As aforementioned compared with traditional income inequality measures, such as Gini coefficient, top income shares directly indicate income discrepancy between the rich and the poor and thus can provide more intuitive understandings on income inequality (Piketty, 2014). Moreover, given that the empirical model of this study is based on the neoclassical growth model with log of per capita income as the dependent variable, and the log of top income shares indicate log-differences of per capita income between the rich and entire population, top income shares are more suitable equity measures for this study compared with other variables, such as the Gini coefficient. Moreover, the equity measures of this study are based on (pre-tax) market income instead of disposable (post-tax) income, given that financialization and innovation are more closely related to pre-tax income rather than post-tax income, and pre-tax top income shares provide greater availability than post-tax ones. Particularly, post-tax measures inevitably include the redistribution impact of each country, and the policy effect practically function as a noise in the analysis focusing on pre-tax income inequality.

Regarding the measure of technological innovation, this study utilizes per capita United States patent grants weighted by citation received after their application. The citation-weighted patent size measure is first proposed and utilized by Hall et al. (2001a, 2005), and it was also adopted by Aghion et al. (2018), who discussed the equity impact of technological innovation. Thus, by introducing the same measure of innovation, this study compares the empirical findings from the panel structural VAR analysis to those from the cross-sectional panel analysis of Aghion et al. (2018). Specifically, the United States patent grants are measured in their application years, the measure considers different citation propensities across citing and cited years and technological fields, and the truncation bias is adjusted by following Hall et al. (2001a, 2001b). Particularly, in contrast with Aghion et al. (2018) who utilized citations within five years after application for the weighing patents, this study weights patent grants with citations of up to 20 years after their application, which seems to be more appropriate considering the distributions of citation lag discussed by Hall et al. (2001a, 2005).

In measuring financialization, this study introduces measures and indices related to stock market. Specifically, this study utilizes stock market capitalization and stock market total value traded (logged ratio to aggregate GDP) from the Global Financial Development (hereafter GFD) database provided by World Bank as measures of financialization, which are discussed as financialization measures by Kus (2012) and Alvarez (2015). The stock market measures can reflect financialization in aggregate, given that the financial activities related to non-financial sectors are often conducted through the stock market. Moreover, when they are measured as the ratio to aggregate GDP, they reflect the relative size of financial activity to each country's economy, which are in line with the definition of financialization. In addition to those measures, this study adopts financial market depth index from Financial Development Index (hereafter FDI) dataset provided by the International Monetary Fund (IMF), which envelops various financial market deepening factors, including market capitalization and stock traded volume. In terms of the equity impact of financialization, this study also analyzes the effect of financial development on income inequality by using private credit and liquid liability to GDP ratio (from GFD) and financial institution depth index of FDI. By comparing the impact of financialization and financial development, this study endeavors to clarify whether the equity impact of the financial sector is related to the recent financialization or traditional financial development.

Other variables for specifying the panel structural VAR model, those for the transmission mechanisms, are theoretically originated from neoclassical growth models of Mankiw et al. (1992) and Islam (1995) and growth accounting studies, such as Caselli (2005) and Hall and Jones (1999). First, the physical capital investment factor, log of gross fixed capital formation ratio to aggregate GDP minus logged sum of population growth and capital depreciation rate, is measured using

variables from the Penn World Tables 10.0 (hereafter PWT) (Feenstra et al., 2015). Particularly, while Mankiw et al. (1992) and Islam (1995) calibrated the depreciation rate as 0.03, assumed to be homogenous across time and countries, this study utilizes the depreciation rate of PWT which reflects different rates across countries. Then, by referring to the growth accounting approaches of Caselli (2005), this study measures labor-augmenting productivity growth rate as a Solow residual, which has been calibrated as a constant of 0.02 by Mankiw et al. (1992) and Islam (1995), as follows:

$$\Delta \log z_{it} = (1/(1-\alpha_i)) \cdot \Delta \log Y_{it} - (\alpha_i/(1-\alpha_i)) \cdot \Delta \log K_{it} - \Delta \log N_{it}, \qquad (25)$$

where $\alpha_i = T_i^{-1}\sum_t \alpha_{it}$, and α_{it}, Y_{it}, K_{it}, and N_{it} are capital income share, aggregate GDP, aggregate capital services (stock), and total population, respectively.

4. Estimation Results and Implications

4.1. Distributional Effect of Technological Innovation

The result of the panel time-series LP analysis on the distributional impact of technological innovation is presented in Figure 1 and Table 1:

(Figure 1 and Table 1)

First, regarding the validity of the estimation results, the statistics of Pesaran's (2015a) CD tests on the residuals of LP estimations, presented in Table 1, are indicative of no cross-sectional dependency in error-term, which implies common correlated effects are well controlled by the cross-sectional mean specifications of this study.[4]

In discussing primary estimation results, the cumulative impulse responses of top income shares to the structural shock on citation-weighted United States patents (Figure 1) finds no evidence that technological innovation aggravates income inequality, which is consistent across various patent citation weights (5, 10, and 20 years) and across top income share measures (top 1% and 5%). Particularly, the empirical findings differ from those of Aghion et al. (2018) adopting the same innovation measures in that they indicate the increasing income inequality effect of innovation. Given

[4] Hereafter, unless specifically discussed, the CD tests on LP estimations indicate no cross-sectional dependency in error-term.

that Aghion et al. (2018) also well controlled the endogeneity through instruments, one possible explanation for such difference is the ones related to the empirical methodology and the theoretical scopes utilized by Aghion et al. (2018) and this study: The panel time-series of this study utilizes recursive VAR model, which can consider every possible mechanism of innovation affecting income inequality by allowing feedback effects among all variables. Particularly, given that the transmission mechanism for the equity measures indicating log-differences in per capita income between population groups, this study specifies productivity and capital investment factor, which are the basic determinants of per capita income in neoclassical growth theory and directly affected by technological innovation. Meanwhile, Aghion et al. (2018) focused on a certain equity impact of innovation enhancing monopolistic profits of incumbent entrepreneurs and utilized cross-sectional panel analysis. However, their empirical model failed to consider possible feedback effects between variables and had no solid theoretical basis on specifying control variables.

To discuss more detailed mechanisms that innovation affects income inequality, this study analyzes the responses of labor-augmenting productivity and physical capital investment factor to the innovation shock. The analysis results utilizing top 1% income share as equity measures are presented in Figure 2 and Table 2.

(Figure 2 and Table 2)

The impulse responses of productivity and investment factors reveal that the shock on innovation persistently increases relative labor-augmenting productivity of top income group to aggregate population, but it has no continuing effect on relative physical capital investment. Considering that the shock on productivity is assumed to be determined prior to that on capital investment, and higher productivity increases capital investment, the analysis results indicate that higher innovation activity *potentially* impacts increasing income inequality through labor-augmenting productivity, but such effect can be counteracted by the direct response of physical capital investment assigned to the overall population compared to the rich.

Particularly, the transmission mechanism implications are highly essential in understating the difference between the result of Aghion et al. (2018) and that of this study. The Schumpeterian growth model of Aghion et al. (2018) and Jones and Kim (2018) is fundamentally based on Romer's (1990) product variety model, which does not explicitly consider the factor of physical capital investment. Theoretically, the model of Aghion et al. (2018) assumed the intermediate input of each individual (monopolist) as a linear production function; a product of labor productivity and input. On the basis of neoclassical growth theory, the model of this study explicitly considers the role of physical capital

investment. Such differences in underlying theoretical model are also well revealed in the impulse response analyses: The impulse response of the relative labor-augmenting productivity is in line with the model of Aghion et al. (2018). However, the equity responses in this study differ from the equity effects of Aghion et al. (2018), given that this study additionally considers the role of physical capital investment through the feedback effect mechanisms of recursive VAR specification. Ultimately, the analysis results imply that the panel time-series approach of this study has more advantages than the cross-sectional panel model of Aghion et al. (2018) in that the former can consider more extensive mechanisms of innovation affecting income inequality.

4.2. Equity Impact of Financialization

The estimated impulse response of income inequality to financialization shocks are presented in Figure 3 and Table 3.

(Figure 3 and Table 3)

The analysis on financialization finds that the shocks on various financialization measures increase income inequality measured by top 1% and 5% income shares. Particularly, the shock on financial markets depth index covering various financial market features has persistent effect of increasing income inequality, which is also robust to different inequality measures. Although the findings on financialization-equity model are in line with the findings of Kus (2012), Kwon and Robers (2015), and Alexiou et al. (2021), the contribution of this study lies in discussing the importance of financialization as equity determinants in comparison to the effect of other factors, such as innovation with a single framework. Moreover, in case of the ratio of market capitalization to aggregate GDP (as well as financial markets depth index) particularly reflecting the size of stock (financial) market relative to overall economy, the impulse responses of the relative capital investment for the rich to entire population presented in Figure 4 and Table 4 are indicative of diminishing physical (i.e., fixed) capital investment assigned to the population other than top income group as a channel of financialization aggravating income inequality, which is in line with the theoretical discussions of Kus (2012).[5]

[5] Although the productivity factor (Figure 4) appears to increase in response to the financialization shocks, the CD statistics presented at Table 4 cannot exclude the possibility of cross-sectional dependency.

(Figure 4 and Table 4)

In addition, this study finds that the measures related to financial development, the ratios of private credit and liquid liability to aggregate GDP, and financial institution depth index, have no robust effects on top income shares, which are presented in Figure 5 and Table 5. The additional findings indicate that, rather than general financial development, financialization is a key finance factor related to equity.

(Figure 5 and Table 5)

4.3. Policy Implications for Growth and Equity

To further discuss policy implications, this study additionally analyzes the impulse response of economic growth (measured by log-differenced per capita GDP) to innovation and financialization. The LP specification estimated by this study is as follows:

$$\begin{aligned}\Delta \log y_{it}^{(h)} = \sum_{j=0}^{J} b_{ij,yw}^{(h)} \Delta w_{i(t-j)} + \sum_{j=1}^{J} b_{ij,yz}^{(h)} \Delta \log z_{i(t-j)} + \sum_{j=1}^{J} b_{ij,yx}^{(h)} \Delta \log x_{i(t-j)} \\ + b_{i1,yy}^{(h)} \Delta \log y_{i(t-1)} + \overline{\Delta \log y^{(h)}}_{t} + \overline{\Delta w}_{t} + \tilde{e}_{y,it}^{(h)},\end{aligned} \tag{26}$$

where w_{it} is the variable for financialization or innovation, and the (mean-group) estimator for impulse responses is $\hat{b}_{MG,yw}^{(h)} = N^{-1} \sum_{i=1}^{N} \hat{b}_{i0,yw}^{(h)}$.

In controlling cross-sectional dependency, the impulse responses on economic growth presented in Figure 6 and Table 6 indicate that technological innovation has a persistent effect on log of per capita GDP, which is an indicative of the accelerating effect of innovation on economic growth. Even though such finding is a trivial stylized fact on economic growth, it is an additional contribution of this study as it revisits through a novel empirical framework. Particularly, as discussed above, the panel recursive structural VAR model of this study can address the critiques on cross-sectional (panel) *growth regression* in discussing various growth determinants (Durlauf, 2009). Meanwhile, this study finds no statistically robust responses of per capita GDP to the shock on financialization measures, presented in Figure 7 and Table 7. In interpretating the analysis result, although the shock on market capitalization or financial markets depth index seems to positively affect economic growth, the CD statistics (presented at Table 7) indicate cross-sectional dependency in residual terms and thus possible biasness in estimates.

(Figure 6, Table 6, Figure 7, and Table 7)

In sum, this study finds no evidence that technological innovation aggravates income inequality, nonetheless, it positively impacts economic growth. Meanwhile, financialization is found to aggravate income inequality, but its effect on economic growth remains statistically inconclusive. Accordingly, this provides a policy implication that, contrary to discussions on Schumpeterian studies (or SBTC) literatures, technological innovation can bring Pareto improvements on growth and equity: Promoting innovation accelerates economic growth without the aggravating effect on income inequality. Meanwhile, enhanced financialization increases income inequality without robust evidence of accelerating economic growth.

4.4. Discussions Related to Varieties of Capitalism

Furthermore, the empirical findings provide additional implications related to "Varieties of Capitalism" (hereafter VoC). VoC literatures, such as Hall and Soskice (2001) utilized institutional factors and classified two basic types of capitalism as follows; LMEs (e.g., United States, Canada, and so on) and coordinated market economies (hereafter CMEs; e.g., Germany, Japan, and so on). Regarding detailed features of the capitalism regimes, LMEs show a relatively stronger tendency of financialization (Lazonick, 2010, 2014). Moreover, in the aspect of technological innovation, LMEs have comparative advantages in radical innovation, which is important in fast-moving technology sectors, while incremental innovation, essential in capital goods, prevails in CMEs (Hall and Soskice, 2001; Malik, 2017). In addition, utilizing macroeconomic variables instead of institutional factors, Lee and Shin (2021) derived similar classification to VoC studies and found that LMEs show higher income inequality, whereas LMEs have opposite features.

Regarding VoC and related discussion, the empirical findings of this study provide causal implications on VoC, financialization, and income inequality that, compared with CMEs, deepened the financialization of LMEs results in higher income inequality. In addition, this study analyzes the impacts of radical and incremental innovations on income inequality, which can confirm whether the higher income inequality of LMEs is due to financialization or innovation. In measuring the radicality of innovation, this study refers to Acemoglu et al. (2021), which utilized average citations received per patent within 10 or 20 years of its application (i.e., average quality of patents) and the generality index proposed by Hall et at. (2001b) on the basis of the citation received within 20 years; higher citations per patent or generality implies more radical innovations. Then, this study conducts the LP analysis on the distributional impact of innovation radicality. The result is presented in Figure 8 and

Table 8.

(Figure 8 and Table 8)

The empirical analysis indicates that the shocks on radical innovation, a key innovational feature of LMEs, does not robustly or significantly affect income inequality. Combining the estimation results regarding financialization, the result indicates that a key feature of LMEs leading higher income inequality is financialization rather than (radical) innovations. Moreover, the results re-confirm that financialization is a key determinant of income inequality rather than various characteristics of innovation, given that quality-adjusted size and qualitative measures of innovation are found not to have statistically significant and robust impact on income inequality.

5. Concluding Remarks

Introducing panel structural VAR model with recursive identification and local projections methods for impulse response analysis, this study compares the distributional impact of financialization with that of technological innovation. The methodological contributions of this study lie in proposing a panel recursive VAR model for income inequality and economic growth, which can compare the growth or equity impacts of various factors in a single empirical framework with overcoming the limitations of previous cross-sectional panel analysis. Regarding applicational contributions, the empirical findings indicate no solid evidence of innovation worsening income inequality and financialization increasing top income shares, which differ from Schumpeterian literatures of Aghion et al. (2018) but in line with financialization studies such as Kus (2012), and so on. Particularly, this study finds that the differences between the current study and Aghion et al. (2018) lies in that, by taking advantages of panel recursive VAR model with feedback effects, this study can explicitly consider the equity impact of technological innovation through capital investment which counteracts the potentially aggravating effect through productivity, whereas the latter seems to have only considered the effect through the productivity. Moreover, this study also confirms a mechanism that financialization aggravates income inequality by decreasing fixed capital investment for the overall population other than the rich.

In addition, when combined with the analysis on economic growth, this study finds a Pareto-improving policy of promoting innovation that can accelerate economic growth without compromising income inequality, whereas financialization merely worsens income inequality without

robustly affecting economic growth. Moreover, regarding the discussion on VoC, this study analyzes the impact of radical innovation on income inequality and compares its results with the primary result regarding the financialization-equity analysis: Those estimation results are indicative of financialization (rather than radical innovation) as a link between liberal market economics and higher income inequality.

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Table 1. Cumulative Impulse Responses of Income Inequality to Innovation

Table 1A. Response variable: ΔLn (top 1% income share)

Horizon	0	1	2	3	4	5	6	7	8
Shock	**ΔLn (US patents per capita; 5-yr. citation weight)**								
IR	−0.001	0.020	0.008	−0.005	−0.017	0.025	0.012	−0.002	−0.021
	(0.030)	(0.051)	(0.062)	(0.057)	(0.055)	(0.046)	(0.046)	(0.048)	(0.049)
CD Stat.	0.14	0.54	−0.06	0.68	0.33	−0.39	0.28	−0.35	0.27
Shock	**ΔLn (US patents per capita; 10-yr. citation weight)**								
IR	−0.028	−0.009	0.001	−0.001	−0.059	0.015	0.013	−0.024	−0.058
	(0.027)	(0.037)	(0.039)	(0.043)	(0.060)	(0.050)	(0.047)	(0.047)	(0.046)
CD Stat.	−0.05	0.00	0.14	0.76	0.11	0.51	0.16	−0.29	0.49
Shock	**ΔLn (US patents per capita; 20-yr. citation weight)**								
IR	−0.021	−0.017	0.004	−0.000	−0.034	0.068	0.057	0.018	−0.028
	(0.032)	(0.043)	(0.049)	(0.048)	(0.063)	(0.051)	(0.057)	(0.065)	(0.057)
CD Stat.	−0.13	−0.27	−0.16	1.00	0.11	0.01	0.39	0.24	0.47

Table 1B. Response variable: ΔLn (top 5% income share)

Horizon	0	1	2	3	4	5	6	7	8
Shock	**ΔLn (US patents per capita; 5-yr. citation weight)**								
IR	0.004	0.015	0.009	−0.006	−0.009	0.011	0.004	0.005	0.019
	(0.019)	(0.032)	(0.041)	(0.044)	(0.042)	(0.035)	(0.032)	(0.034)	(0.032)
CD Stat.	0.61	0.30	0.22	0.87	0.57	−0.80	−0.75	−0.49	0.04
Shock	**ΔLn (US patents per capita; 10-yr. citation weight)**								
IR	−0.016	−0.008	−0.004	−0.015	−0.037	−0.008	−0.004	−0.020	−0.024
	(0.016)	(0.023)	(0.026)	(0.034)	(0.040)	(0.036)	(0.034)	(0.034)	(0.032)
CD Stat.	0.35	0.41	0.24	1.28	0.31	0.10	−0.32	−0.68	0.75
Shock	**ΔLn (US patents per capita; 20-yr. citation weight)**								
IR	−0.013	−0.015	−0.005	−0.026	−0.037	0.005	0.022	0.001	−0.013
	(0.016)	(0.026)	(0.028)	(0.035)	(0.043)	(0.036)	(0.036)	(0.035)	(0.032)
CD Stat.	0.74	0.01	0.01	1.05	0.69	−0.15	−0.39	−0.19	0.53

Notes: 1) Standard errors in parentheses.

2) Significance level: * for p<0.1, ** for p<0.05, and *** for p<0.01.

Table 2. Cumulative Impulse Responses of Productivity and Investment Factors in Innovation-Equity Model

Table 2A. Response variable: ΔLn (labor-augmenting productivity; z_{it})

Horizon	0	1	2	3	4	5	6	7	8
Shock	**ΔLn (US patents per capita; 5-yr. citation weight)**								
IR	0.023**	0.042**	0.033	0.042*	0.060***	0.082***	0.106***	0.117***	0.099***
	(0.011)	(0.020)	(0.022)	(0.022)	(0.023)	(0.025)	(0.026)	(0.029)	(0.026)
CD Stat.	−1.16	−0.45	0.02	0.44	0.63	0.61	−0.33	−0.27	−0.29
Shock	**ΔLn (US patents per capita; 10-yr. citation weight)**								
IR	0.013	0.035**	0.028	0.040*	0.060**	0.087***	0.115***	0.117***	0.101***
	(0.012)	(0.018)	(0.023)	(0.023)	(0.026)	(0.026)	(0.027)	(0.028)	(0.026)
CD Stat.	−0.34	0.56	1.61	1.93	1.99	1.93	1.18	0.74	1.12
Shock	**ΔLn (US patents per capita; 20-yr. citation weight)**								
IR	0.009	0.025	0.009	0.013	0.029	0.054**	0.082***	0.087***	0.075***
	(0.012)	(0.017)	(0.020)	(0.022)	(0.022)	(0.024)	(0.024)	(0.025)	(0.023)
CD Stat.	−0.50	0.07	1.05	1.27	1.23	1.30	1.20	1.18	1.58

Table 2B. Response variable: ΔLn (physical capital investment factor; x_{it})

Horizon	0	1	2	3	4	5	6	7	8
Shock	**ΔLn (US patents per capita; 5-yr. citation weight)**								
IR	0.020	0.053**	0.007	−0.024	0.007	0.055	0.044	0.061	0.082
	(0.015)	(0.027)	(0.036)	(0.057)	(0.046)	(0.058)	(0.061)	(0.062)	(0.057)
CD Stat.	0.38	−0.65	−0.82	−0.78	−0.49	−1.08	−1.50	−1.16	−0.38
Shock	**ΔLn (US patents per capita; 10-yr. citation weight)**								
IR	0.030*	0.060*	0.014	0.007	0.013	0.046	0.044	0.055	0.049
	(0.016)	(0.031)	(0.036)	(0.055)	(0.050)	(0.063)	(0.063)	(0.063)	(0.064)
CD Stat.	0.16	−0.83	−0.98	−1.01	−0.57	−1.20	−0.88	−1.34	−0.49
Shock	**ΔLn (US patents per capita; 20-yr. citation weight)**								
IR	0.028	0.047*	0.023	0.022	0.033	0.080	0.052	0.031	0.030
	(0.018)	(0.027)	(0.037)	(0.051)	(0.050)	(0.070)	(0.065)	(0.074)	(0.066)
CD Stat.	−0.15	−0.97	−1.13	−0.96	−0.38	−0.73	−0.82	−0.86	−0.42

Notes: See Table 1.

Table 3. Cumulative Impulse Responses of Income Inequality to Financialization

Table 3A. Response variable: ΔLn (top 1% income share)

Horizon	0	1	2	3	4	5	6	7	8
Shock	**ΔLn (Stock market capitalization; ratio to total GDP)**								
IR	0.058	0.138*	0.111	0.148**	0.085	0.018	0.108	0.132**	0.137*
	(0.037)	(0.080)	(0.077)	(0.061)	(0.065)	(0.055)	(0.084)	(0.064)	(0.070)
CD Stat.	−0.77	−0.23	0.57	0.11	0.24	0.75	0.39	0.08	0.49
Shock	**ΔLn (Stock market total traded value; ratio to total GDP)**								
IR	0.034	0.042	0.082**	0.106***	0.077*	0.082*	0.119**	0.159***	0.106*
	(0.030)	(0.048)	(0.039)	(0.039)	(0.044)	(0.048)	(0.048)	(0.044)	(0.055)
CD Stat.	−0.62	−0.86	−0.14	0.49	0.13	0.13	−0.05	−0.63	−0.02
Shock	**ΔLn (Financial market depth; index)**								
IR	0.050	0.059	0.108**	0.196***	0.202***	0.200***	0.215***	0.269***	0.243**
	(0.034)	(0.094)	(0.054)	(0.046)	(0.053)	(0.068)	(0.068)	(0.090)	(0.109)
CD Stat.	−0.41	−0.03	0.39	0.94	0.65	0.24	0.62	1.11	1.66

Table 3B. Response variable: ΔLn (top 5% income share)

Horizon	0	1	2	3	4	5	6	7	8
Shock	**ΔLn (Stock market capitalization; ratio to total GDP)**								
IR	0.024	0.071*	0.067	0.108***	0.013	0.015	0.021	0.087**	0.081*
	(0.020)	(0.037)	(0.042)	(0.030)	(0.060)	(0.032)	(0.035)	(0.037)	(0.048)
CD Stat.	−1.46	−0.14	0.47	−0.11	−0.48	0.21	−0.23	−0.79	−1.46
Shock	**ΔLn (Stock market total traded value; ratio to total GDP)**								
IR	0.022	0.030	0.038	0.059***	0.031	0.039	0.032	0.065**	0.043
	(0.016)	(0.027)	(0.026)	(0.022)	(0.027)	(0.029)	(0.025)	(0.025)	(0.032)
CD Stat.	−1.66	−1.82	−0.84	−0.16	−0.44	−0.43	−0.88	−0.91	−0.88
Shock	**ΔLn (Financial market depth; index)**								
IR	0.037	0.045	0.062**	0.081***	0.094***	0.104***	0.094***	0.084*	0.111**
	(0.025)	(0.036)	(0.027)	(0.023)	(0.033)	(0.037)	(0.034)	(0.049)	(0.052)
CD Stat.	−0.67	−0.54	0.41	1.10	0.64	−0.63	−0.54	−0.19	0.40

Notes: See Table 1.

Table 4. Cumulative Impulse Responses of Productivity and Investment Factors in Financialization-Equity Model

Table 4A. Response variable: ΔLn (labor-augmenting productivity; z_{it})

Horizon	0	1	2	3	4	5	6	7	8
Shock	**ΔLn (Stock market capitalization; ratio to total GDP)**								
IR	0.049***	0.131***	0.193***	0.170***	0.123	0.143	0.193*	0.197*	0.227*
	(0.019)	(0.049)	(0.069)	(0.065)	(0.081)	(0.102)	(0.115)	(0.106)	(0.125)
CD Stat.	−0.16	0.67	1.82	1.72	1.82	2.52	2.51	2.89	3.92
Shock	**ΔLn (Stock market total traded value; ratio to total GDP)**								
IR	0.019*	0.015	0.023	0.024	0.016	0.009	0.027	0.031	0.044
	(0.011)	(0.020)	(0.023)	(0.029)	(0.025)	(0.030)	(0.028)	(0.035)	(0.037)
CD Stat.	0.00	0.15	1.84	1.84	1.97	2.30	2.11	3.50	3.73
Shock	**ΔLn (Financial market depth; index)**								
IR	0.014	0.069***	0.068**	0.073	0.070	0.083	0.095	0.144	0.151
	(0.011)	(0.021)	(0.031)	(0.047)	(0.068)	(0.082)	(0.074)	(0.101)	(0.093)
CD Stat.	0.40	0.17	0.90	1.25	1.36	1.44	1.60	2.16	2.89

Table 4B. Response variable: ΔLn (physical capital investment factor; x_{it})

Horizon	0	1	2	3	4	5	6	7	8
Shock	**ΔLn (Stock market capitalization; ratio to total GDP)**								
IR	0.018	0.097**	0.142**	0.133*	0.169**	0.180**	0.190**	0.189***	0.137**
	(0.027)	(0.040)	(0.056)	(0.071)	(0.076)	(0.076)	(0.075)	(0.064)	(0.058)
CD Stat.	−0.77	−0.32	−0.31	0.32	−0.15	0.74	0.25	−0.43	−0.36
Shock	**ΔLn (Stock market total traded value; ratio to total GDP)**								
IR	−0.021	0.054**	0.036	0.041	0.044	0.053	0.091	0.072	0.054
	(0.019)	(0.027)	(0.030)	(0.035)	(0.043)	(0.045)	(0.067)	(0.057)	(0.043)
CD Stat.	0.00	0.11	−0.82	−1.24	−0.82	−0.01	0.28	−0.47	−0.52
Shock	**ΔLn (Financial market depth; index)**								
IR	−0.010	0.032	0.057*	0.103**	0.113*	0.132	0.154**	0.108*	0.083*
	(0.025)	(0.034)	(0.034)	(0.047)	(0.066)	(0.082)	(0.078)	(0.065)	(0.045)
CD Stat.	0.32	0.02	−0.03	0.81	0.27	0.38	−0.08	−0.45	−0.55

Notes: See Table 1.

Table 5. Cumulative Impulse Responses of Income Inequality to Financial Development

Table 5A. Response variable: ΔLn (top 1% income share)

Horizon	0	1	2	3	4	5	6	7	8
Shock	**ΔLn (Private credit; ratio to total GDP)**								
IR	−0.010	0.131	0.100	0.181	0.120	0.058	−0.026	−0.012	0.001
	(0.067)	(0.125)	(0.126)	(0.166)	(0.185)	(0.227)	(0.228)	(0.199)	(0.192)
CD Stat.	−0.65	−0.27	−0.41	−0.20	1.00	0.73	0.09	0.43	0.28
Shock	**ΔLn (Liquid liabilities; ratio to total GDP)**								
IR	−0.284**	−0.121	0.007	−0.004	−0.129	−0.230	−0.176	−0.192	−0.137
	(0.131)	(0.186)	(0.191)	(0.173)	(0.160)	(0.175)	(0.161)	(0.197)	(0.184)
CD Stat.	−1.31	−0.97	−1.29	−0.16	−0.02	−0.47	−0.30	−0.08	0.10
Shock	**ΔLn (Financial institution depth; index)**								
IR	0.189	−0.028	0.066	0.066	−0.044	−0.052	−0.040	0.029	−0.051
	(0.137)	(0.178)	(0.158)	(0.184)	(0.197)	(0.202)	(0.175)	(0.178)	(0.187)
CD Stat.	−0.02	−0.23	−0.65	−0.27	−0.23	−0.07	0.21	1.23	2.17

Table 5B. Response variable: ΔLn (top 5% income share)

Horizon	0	1	2	3	4	5	6	7	8
Shock	**ΔLn (Private credit; ratio to total GDP)**								
IR	0.003	0.107*	0.123*	0.119	0.082	0.106	0.033	−0.002	0.001
	(0.042)	(0.062)	(0.074)	(0.090)	(0.093)	(0.117)	(0.120)	(0.112)	(0.107)
CD Stat.	0.15	−0.40	−0.76	0.53	0.36	0.44	0.65	0.91	0.73
Shock	**ΔLn (Liquid liabilities; ratio to total GDP)**								
IR	−0.103	−0.063	0.023	−0.024	−0.071	−0.116	−0.083	−0.101	−0.108
	(0.066)	(0.096)	(0.097)	(0.096)	(0.099)	(0.097)	(0.097)	(0.112)	(0.114)
CD Stat.	−1.13	−0.84	−0.62	−0.10	0.18	−0.17	−0.11	−0.49	−0.17
Shock	**ΔLn (Financial institution depth; index)**								
IR	0.138**	0.065	0.163	0.164	0.078	0.039	0.048	0.093	0.066
	(0.070)	(0.104)	(0.106)	(0.119)	(0.121)	(0.132)	(0.110)	(0.129)	(0.128)
CD Stat.	0.37	−0.18	−0.14	−0.68	−0.04	−0.54	0.13	0.97	1.87

Notes: See Table 1.

Table 6. Cumulative Impulse Responses of Economic Growth to Innovation

	Response variable: ΔLn (per capita GDP)								
Horizon	0	1	2	3	4	5	6	7	8
Shock	**ΔLn (US patents per capita; 5-yr. citation weight)**								
IR	0.009	0.025**	0.026**	0.026	0.038	0.064***	0.081***	0.082***	0.076**
	(0.007)	(0.010)	(0.012)	(0.016)	(0.025)	(0.025)	(0.025)	(0.027)	(0.031)
CD Stat.	1.30	0.54	0.96	0.24	−0.31	0.40	0.17	0.82	1.25
Shock	**ΔLn (US patents per capita; 10-yr. citation weight)**								
IR	0.012	0.032***	0.040**	0.041**	0.053**	0.084***	0.101***	0.099***	0.099***
	(0.009)	(0.012)	(0.016)	(0.017)	(0.022)	(0.026)	(0.027)	(0.027)	(0.032)
CD Stat.	0.26	0.24	0.44	−0.04	0.25	0.77	−0.01	−0.16	−0.17
Shock	**ΔLn (US patents per capita; 20-yr. citation weight)**								
IR	0.018**	0.038***	0.040***	0.039**	0.055	0.099**	0.118***	0.134**	0.119**
	(0.009)	(0.011)	(0.014)	(0.019)	(0.034)	(0.045)	(0.044)	(0.057)	(0.053)
CD Stat.	0.71	0.56	0.40	−0.20	−0.44	−0.41	−0.67	−0.54	−0.22

Notes: See Table 1.

Table 7. Cumulative Impulse Responses of Economic Growth to Financialization

	Response variable: ΔLn (per capita GDP)								
Horizon	0	1	2	3	4	5	6	7	8
Shock	**ΔLn (Stock market capitalization; ratio to total GDP)**								
IR	0.013	0.070***	0.106***	0.134***	0.126***	0.131***	0.151***	0.142***	0.135***
	(0.009)	(0.014)	(0.028)	(0.035)	(0.036)	(0.036)	(0.048)	(0.049)	(0.043)
CD Stat.	0.81	2.05	3.64	2.95	3.36	2.94	2.14	2.07	2.75
Shock	**ΔLn (Stock market total traded value; ratio to total GDP)**								
IR	−0.008	−0.002	−0.001	0.005	−0.009	0.008	0.014	0.020	0.036
	(0.009)	(0.012)	(0.019)	(0.022)	(0.026)	(0.023)	(0.025)	(0.024)	(0.025)
CD Stat.	2.54	1.59	2.49	2.54	3.28	3.05	2.87	3.48	3.20
Shock	**ΔLn (Financial market depth; index)**								
IR	0.012	0.050**	0.066*	0.087*	0.082	0.083	0.087	0.083	0.063
	(0.012)	(0.021)	(0.034)	(0.046)	(0.055)	(0.061)	(0.060)	(0.055)	(0.048)
CD Stat.	1.12	1.90	2.46	2.74	2.02	1.46	2.10	2.55	2.82

Notes: See Table 1.

Table 8. Cumulative Impulse Responses of Income Inequality to Radical Innovation

Table 8A. Response variable: ΔLn (top 1% income share)

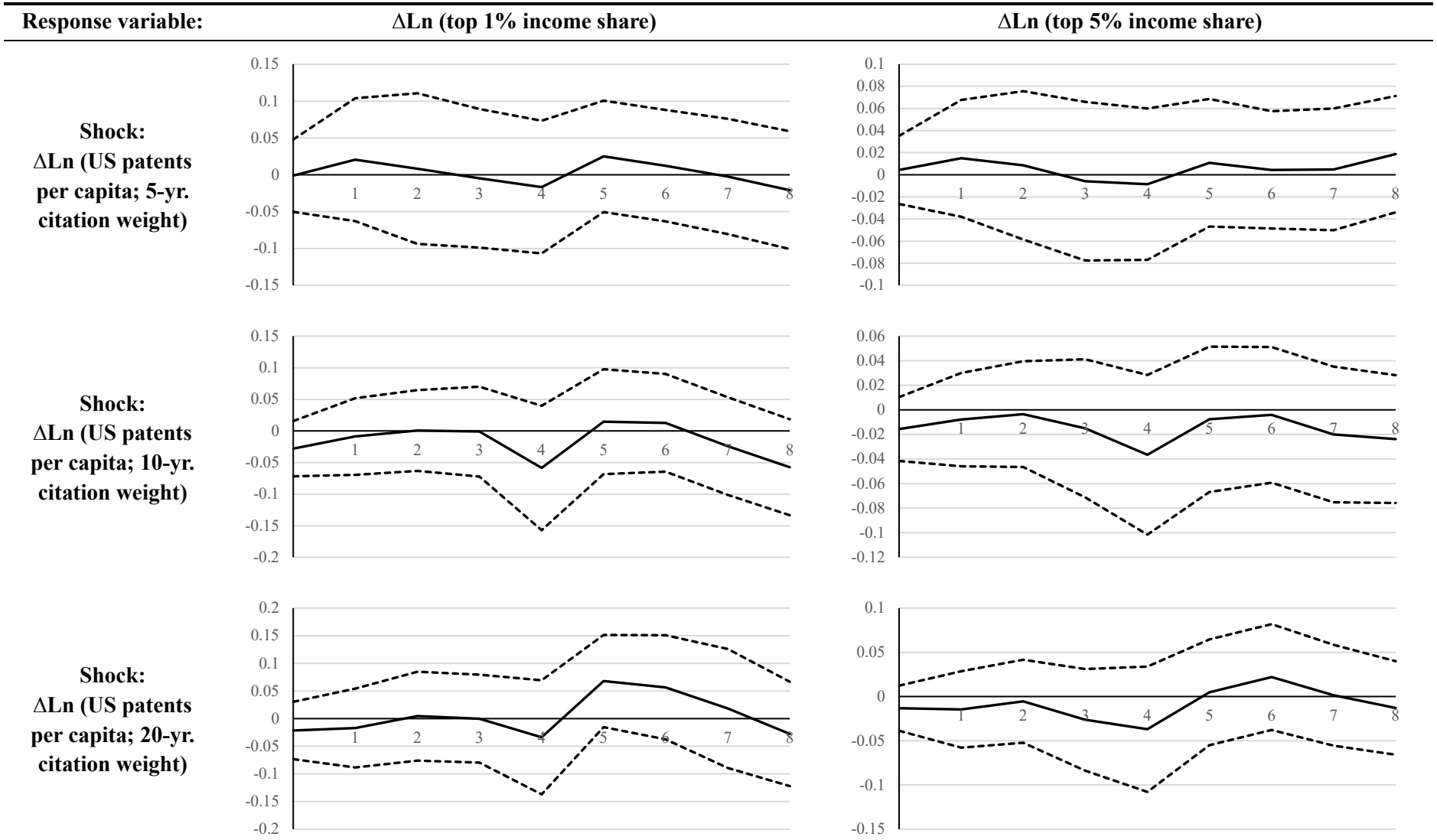
Horizon	0	1	2	3	4	5	6	7	8
Shock	**ΔLn (Citation per patents; received within 10 years)**								
IR	−0.031	−0.049	−0.027	−0.014	−0.037	0.031	0.018	0.003	−0.003
	(0.032)	(0.044)	(0.054)	(0.049)	(0.046)	(0.047)	(0.050)	(0.052)	(0.052)
CD Stat.	−0.58	−0.54	0.87	1.37	0.54	−0.09	−0.56	0.56	1.72
Shock	**ΔLn (Citation per patents; received within 20 years)**								
IR	−0.075*	−0.097	−0.013	−0.058	−0.099	0.012	0.023	−0.030	−0.101
	(0.045)	(0.063)	(0.074)	(0.080)	(0.077)	(0.069)	(0.091)	(0.069)	(0.078)
CD Stat.	−0.59	−0.68	0.28	1.10	0.51	0.15	−0.09	0.19	1.98
Shock	**ΔLn (Generality index)**								
IR	−0.031	0.010	0.005	0.022	0.019	0.113	0.103	−0.006	0.086
	(0.103)	(0.118)	(0.121)	(0.180)	(0.150)	(0.143)	(0.177)	(0.131)	(0.132)
CD Stat.	−0.42	0.27	−0.10	1.25	0.80	0.95	0.34	0.55	1.00

Table 8B. Response variable: ΔLn (top 5% income share)

Horizon	0	1	2	3	4	5	6	7	8
Shock	**ΔLn (Citation per patents; received within 10 years)**								
IR	−0.017	−0.030	−0.016	−0.034	−0.011	0.022	−0.001	−0.007	−0.001
	(0.019)	(0.028)	(0.034)	(0.034)	(0.030)	(0.027)	(0.034)	(0.037)	(0.029)
CD Stat.	−0.99	−1.28	−0.12	0.92	−0.07	−0.45	−0.53	−0.19	1.08
Shock	**ΔLn (Citation per patents; received within 20 years)**								
IR	−0.044**	−0.050	−0.005	−0.025	−0.052	0.004	0.020	0.001	−0.034
	(0.021)	(0.032)	(0.045)	(0.054)	(0.045)	(0.043)	(0.050)	(0.045)	(0.041)
CD Stat.	0.21	−1.15	−0.08	0.31	−0.19	−0.52	−0.72	−0.43	1.21
Shock	**ΔLn (Generality index)**								
IR	−0.007	−0.013	−0.007	−0.010	−0.006	0.039	0.066	0.024	0.089
	(0.049)	(0.078)	(0.073)	(0.107)	(0.080)	(0.080)	(0.080)	(0.088)	(0.078)
CD Stat.	−0.74	0.22	−0.41	1.27	0.30	0.10	−0.25	−0.00	0.40

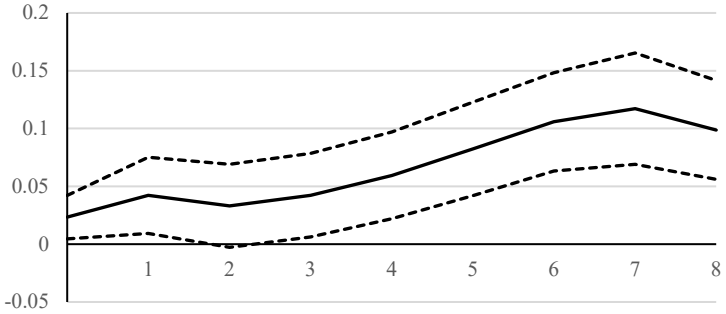
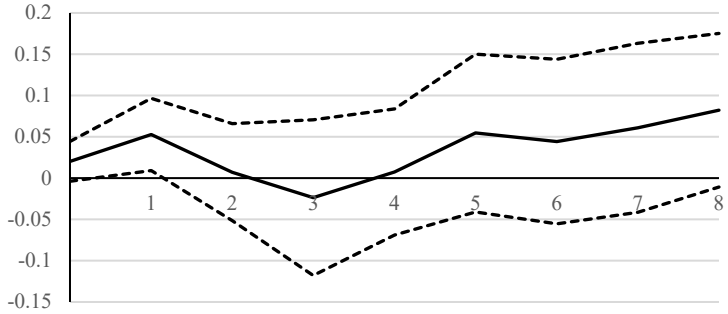
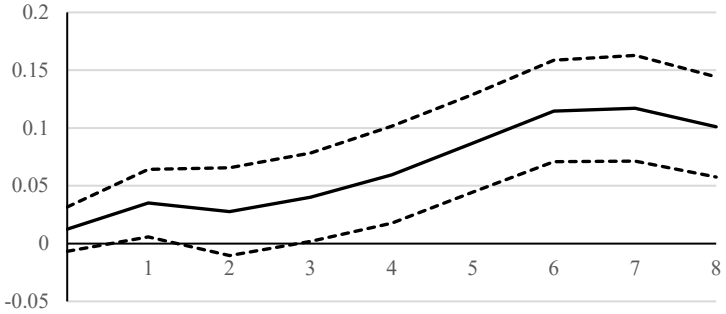
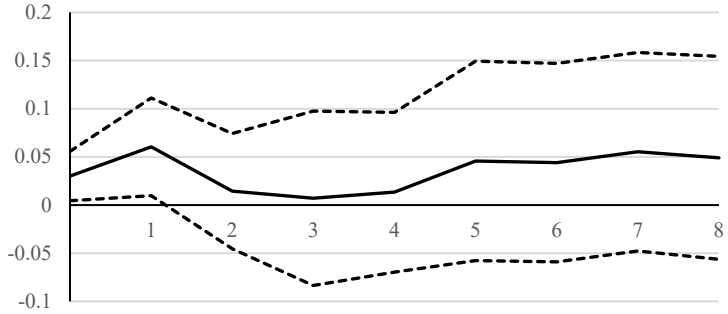
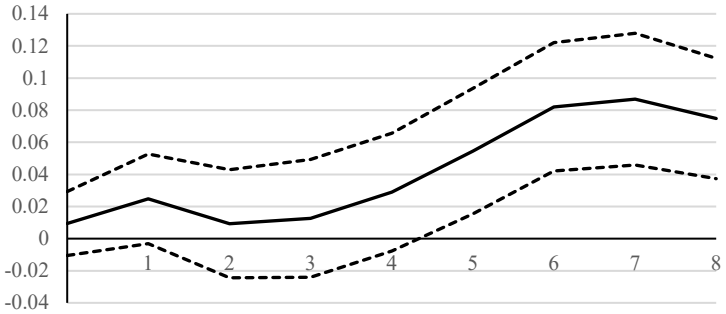
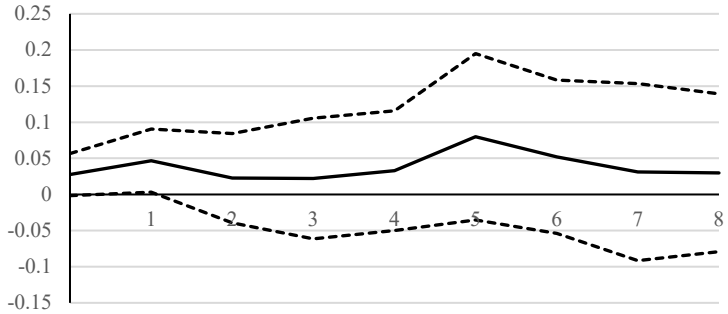
Notes: See Table 1.

Figure 1: Cumulative Impulse Responses of Income Inequality to Innovation



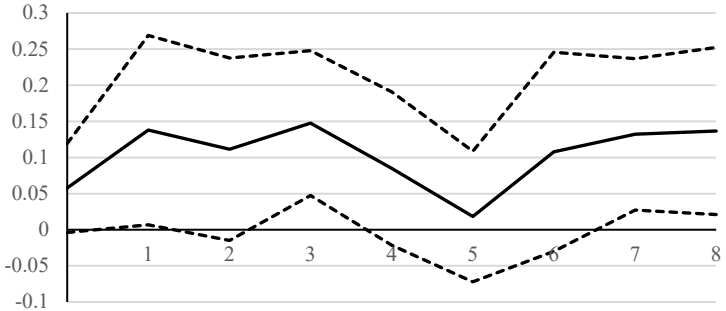
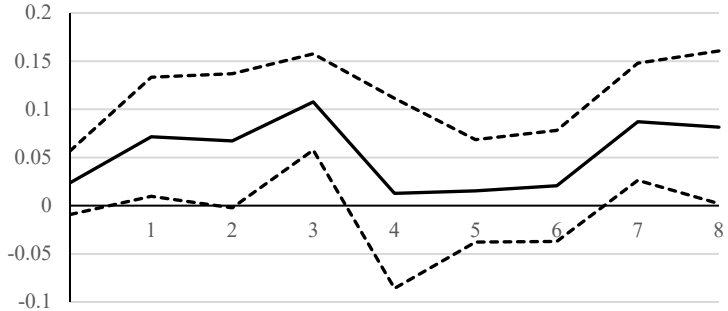
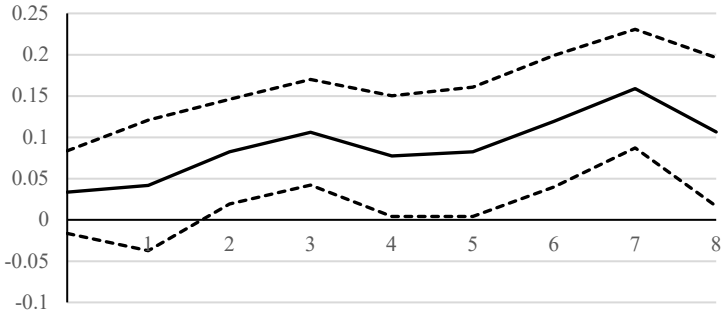
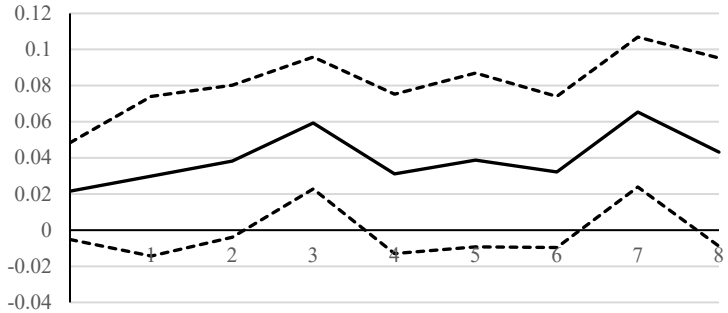
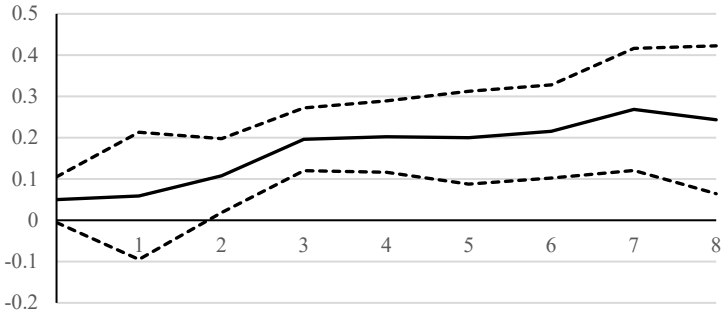
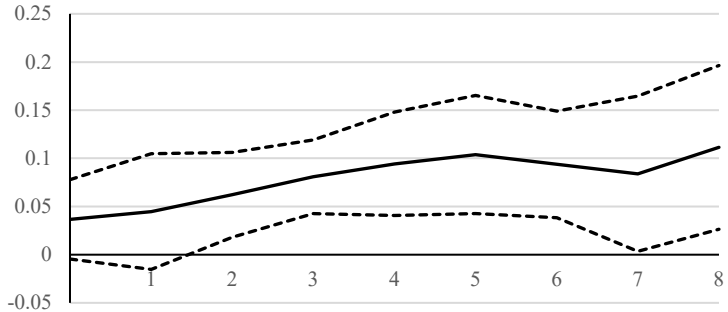
Note: 1) Dotted lines indicate 90% confidence intervals.

Figure 2: Cumulative Impulse Responses of Productivity and Investment Factors in Innovation-Equity Model

Response variable:	ΔLn (labor-augmenting productivity; z_{it})	ΔLn (physical investment factor; x_{it})
Shock: ΔLn (US patents per capita; 5-yr. citation weight)		
Shock: ΔLn (US patents per capita; 10-yr. citation weight)		
Shock: ΔLn (US patents per capita; 20-yr. citation weight)		

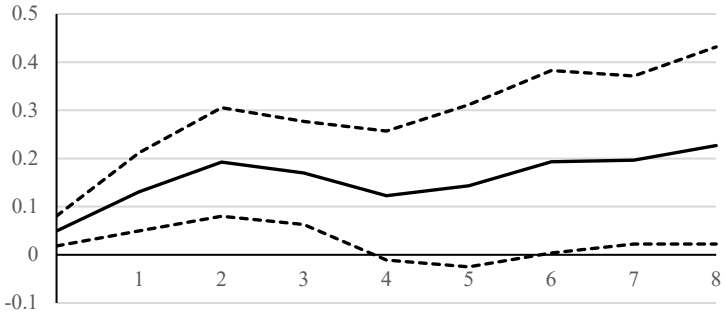
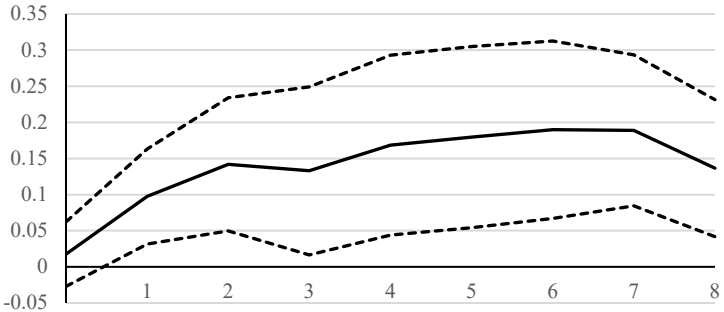
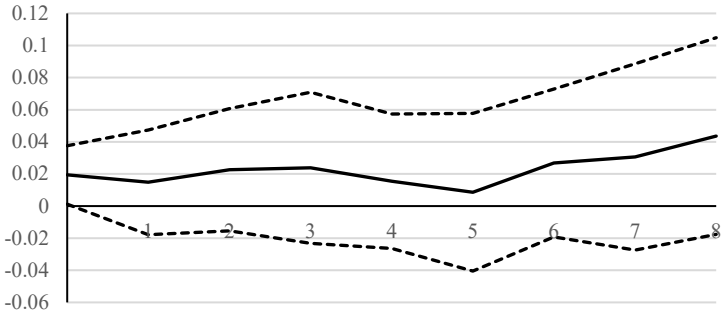
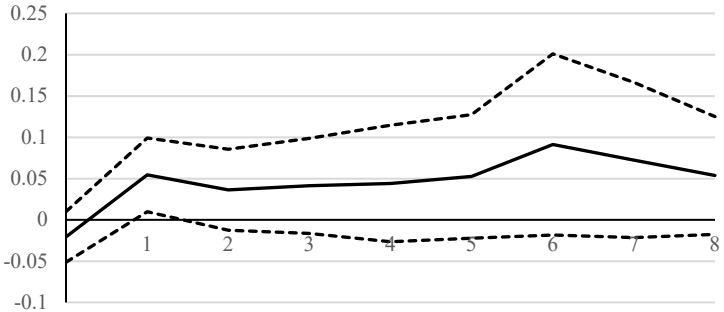
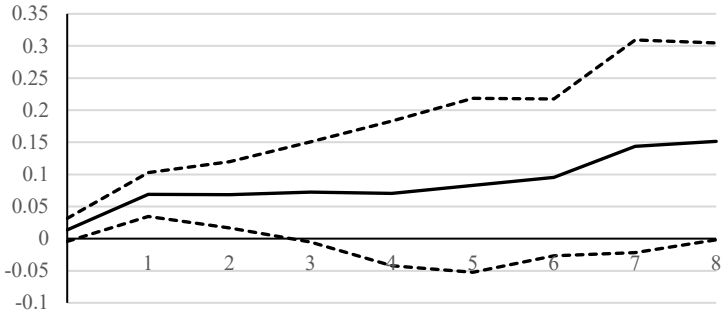
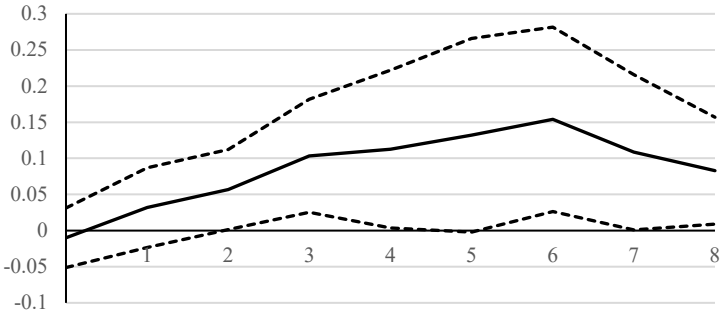
Note: See Figure 1.

Figure 3: Cumulative Impulse Responses of Income Inequality to Financialization

Response variable:	ΔLn (top 1% income share)	ΔLn (top 5% income share)
Shock: ΔLn (Stock market capitalization; ratio to total GDP)		
Shock: ΔLn (Stock market total traded value; ratio to total GDP)		
Shock: ΔLn (Financial market depth; index)		

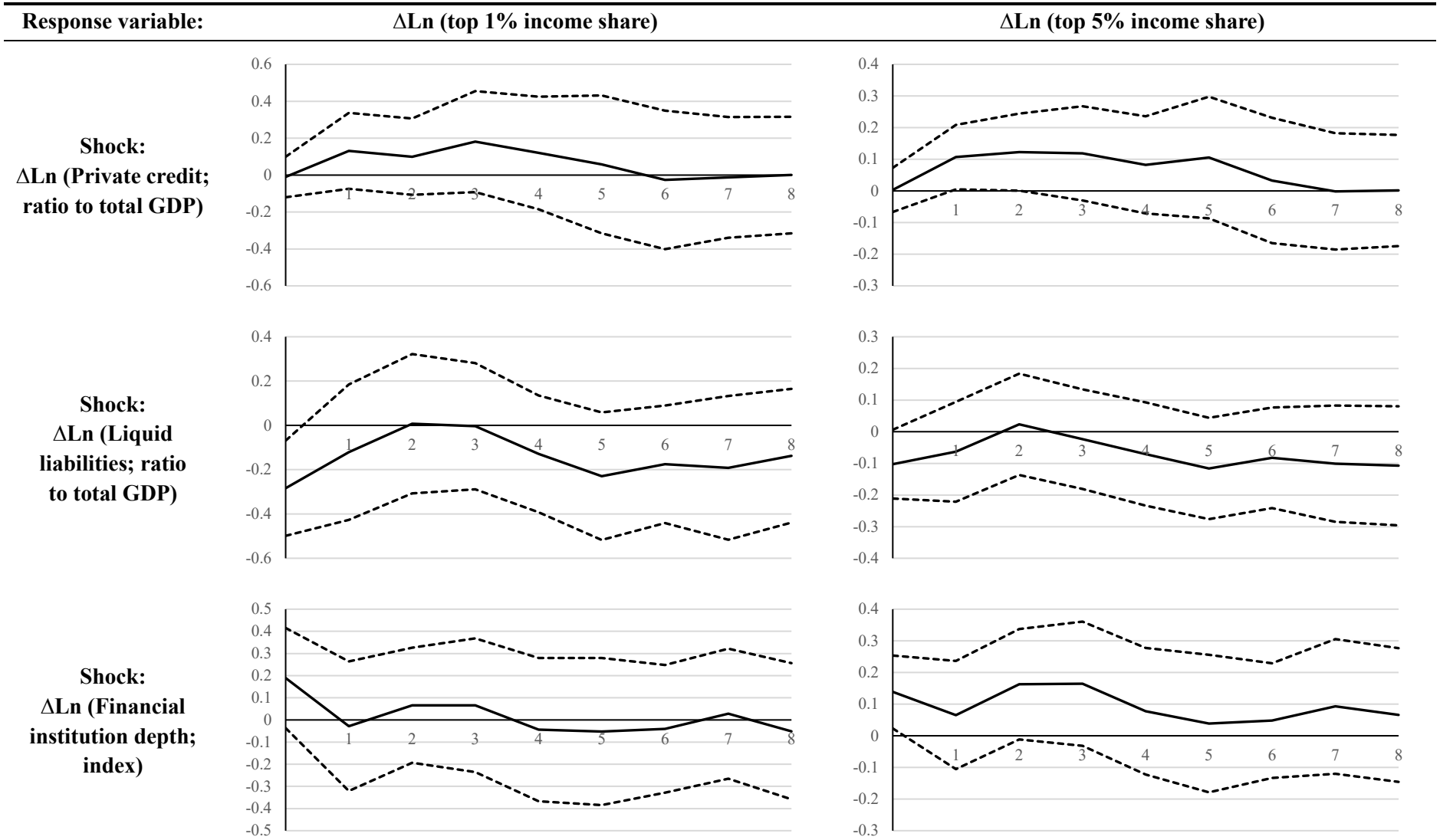
Note: See Figure 1.

Figure 4: Cumulative Impulse Responses of Productivity and Investment Factors in Financialization-Equity Model

Response variable:	ΔLn (labor-augmenting productivity; z_{it})	ΔLn (physical investment factor; x_{it})
Shock: ΔLn (Stock market capitalization; ratio to total GDP)		
Shock: ΔLn (Stock market total traded value; ratio to total GDP)		
Shock: ΔLn (Financial market depth; index)		

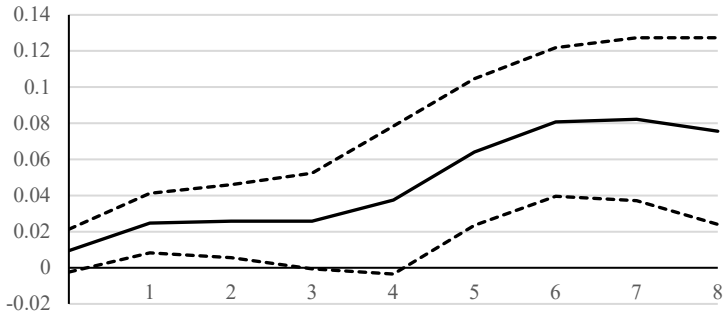
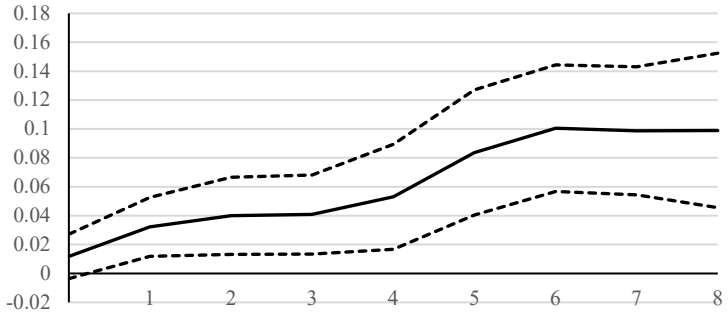
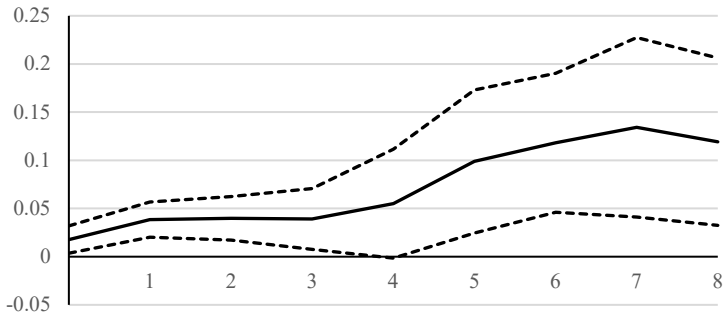
Note: See Figure 1.

Figure 5: Cumulative Impulse Responses of Income Inequality to Financial Development



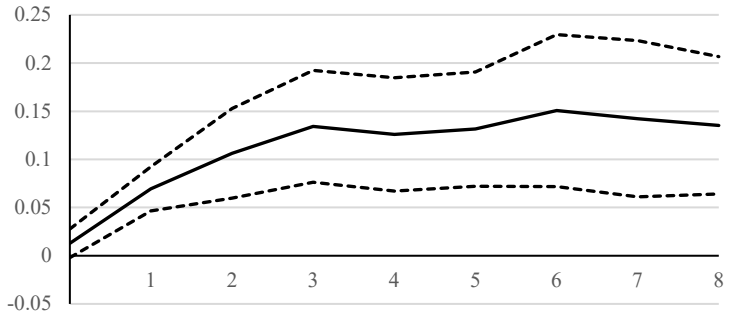
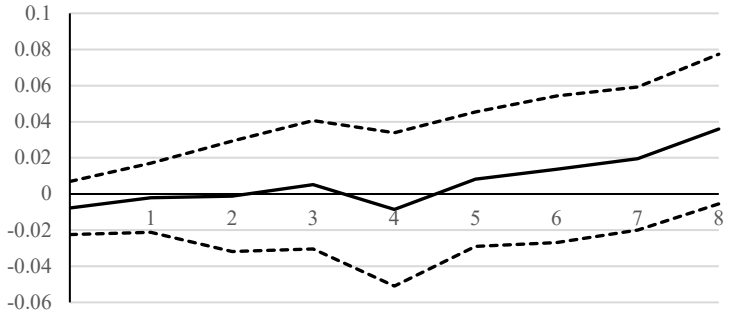
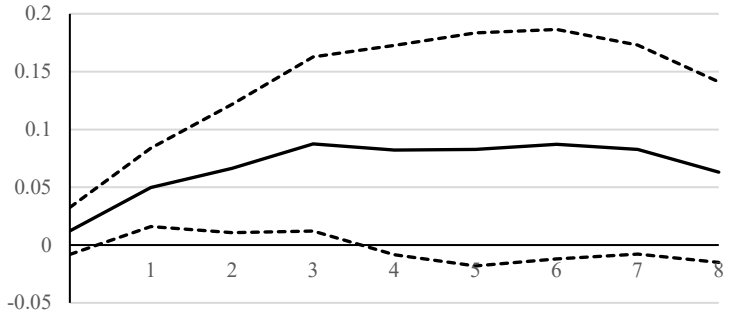
Note: See Figure 1.

Figure 6. Cumulative Impulse Responses of Economic Growth to Innovation

Response variable:	ΔLn (per capita GDP)
Shock: ΔLn (US patents per capita; 5-yr. citation weight)	
Shock: ΔLn (US patents per capita; 10-yr. citation weight)	
Shock: ΔLn (US patents per capita; 20-yr. citation weight)	

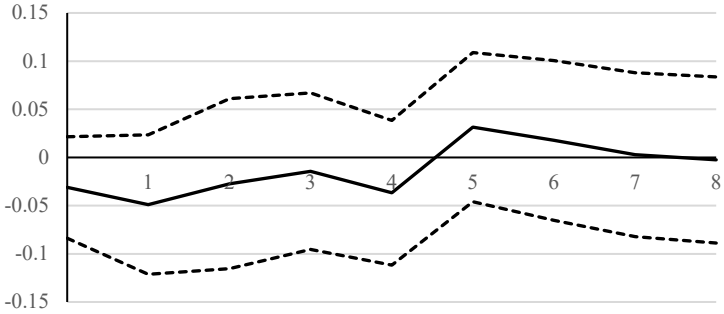
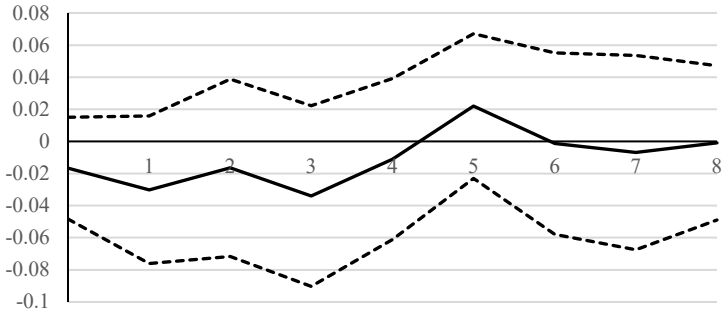
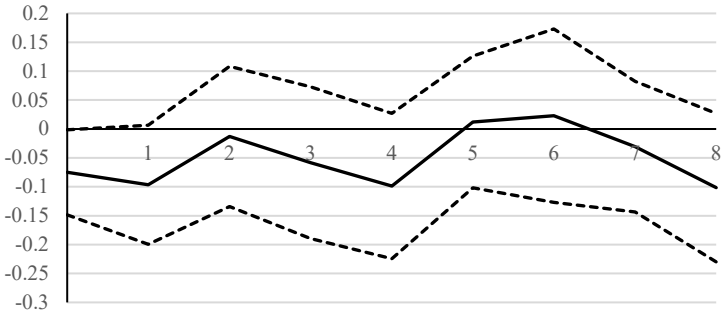
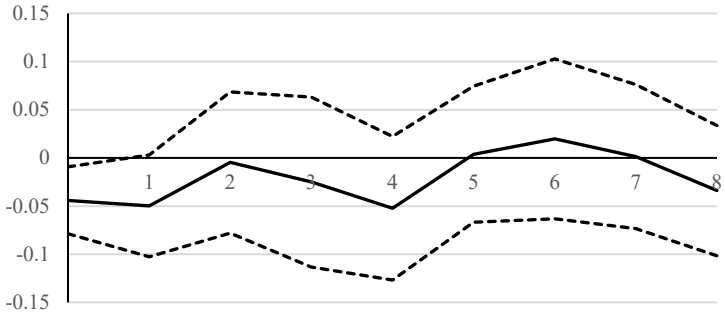
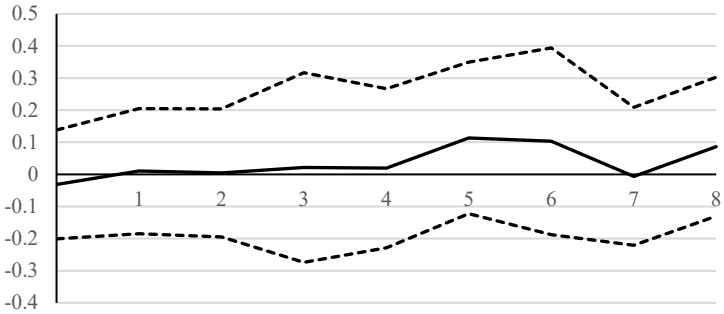
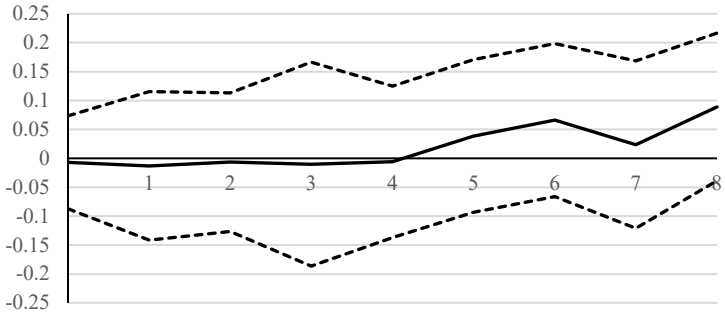
Note: See Figure 1.

Figure 7. Cumulative Impulse Responses of Economic Growth to Financialization

Response variable:	ΔLn (per capita GDP)
Shock: ΔLn (Stock market capitalization; ratio to total GDP)	
Shock: ΔLn (Stock market total traded value; ratio to total GDP)	
Shock: ΔLn (Financial market depth; index)	

Note: See Figure 1.

Figure 8: Cumulative Impulse Responses of Income Inequality to Radical Innovation

Response variable:	ΔLn (top 1% income share)	ΔLn (top 5% income share)
Shock: ΔLn (Citation per patents; received within 10 years)		
Shock: ΔLn (Citation per patents; received within 20 years)		
Shock: ΔLn (Generality index)		

Note: See Figure 1.