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The Impact of Multi-Factor Productivity on Income Inequality*

Takashi KAMIHIGASHI
Yosuke SASAKI

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Research Institute for Economics and Business Administration
Kobe University
2-1 Rokkodai, Nada, Kobe 657-8501 JAPAN

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Takashi Kamihigashi *& *Yosuke Sasaki* †

Abstract

Numerous empirical studies suggest that a technology change is associated with an increase in income inequality. The Gini coefficient (or the Gini index) is commonly calculated to quantify income inequality and analyze the relationship between inequality and other economic variables. However, the availability of Gini index data in a time series (e.g., five-year data) is sparse. Thus, it is difficult to study dynamic effects in panel data. This study utilizes the relative share of income as an inequality measure to analyze the interactions between cross-country income inequality and multi-factor productivity. Additional economic variables are also considered to inform the analysis further. Using the relative share of income enables observation of the long-term relationship dynamics between the two variables of interest because the necessary data are available for individual countries. Panel data are also available for cross-country factors. This study is the first to show that multi-factor productivity has a relationship with income inequality, based on understanding the static and dynamic effects. This study defines a model with some lags of the variable to capture the "dynamic effects." The estimation method is the panel vector autoregression (Sigmund & Ferstl (2019)[35]) with generalized method of moments (Blundell & Bond (1998)[4]). This method determines the multi-period structure of multi-factor productivity and income inequality. Overall, this approach identifies the dynamic effects of multi-factor productivity on income distribution, which is a novel finding that requires further analysis.

Keywords: Income Inequality, Muti-Factor Productivity, Cross-Country, & Panel Vector Autoregression

1 Introduction

Since the financial crisis of 2007/08, the world has experienced social and political turmoil. This turmoil is perceived to have caused changes in income distribution, though it is argued that changes have occurred since the 1980s, and the financial crisis exacerbated them. Because of the popularity of Piketty's (2015)[31] 's argument that the economic system based on the concept of globalization favors the rich, uneven income distribution is now frequently considered to be a significant societal problem.

To explain inequality in income distribution, several researchers have focused on interactions among variables, such as the Gini index, financial development (Piketty (2015)[31], Jauch & Watzka (2016)[20]), government spending in the economy (Jauch & Watzka (2016)[20] also use as the control variable), trade openness (Daumal (2013)[11]) using cross-country panel data or time-series analyses of a single country. Then, this study estimates the relationship between the top 1% income bracket, multi-factor productivity, financial development, government spending, and trade openness. The objective of including multi-factor

*Center for Computational Social Science, Kobe University
†Center for Computational Social Science, Kobe University

productivity is to account for technological change's impact on income inequality/distribution in cross-country analysis. As for technological change's effect on income inequality/distribution, several researchers find a positive relationship between wage dispersion and skill-biased technological change (Berman et al. (1998)[3]). However, there are few findings on the interaction between multi-factor productivity and income inequality/distribution in the macroeconometric literature.

Jaumotte et al. (2013)[21] discovered that increasing trade and financial globalization had separately identifiable and opposite effects on the income distribution. Trade liberalization and export growth were associated with lower income inequality, whereas increased financial openness was associated with higher inequality. However, Bergh and Nilsson (2010)[2] reported that trade liberalization and economic globalization increased income inequality. Conflicting results such as these explain the large body of literature focusing on financial development and the economic variables.

The primary contributions of the extant literature include the panel data analysis focusing time series on income shares using the panel vector autoregression model (panel VAR) (Sigmund & Ferstl (2019)[35]).

Building on previous studies, this study estimates the dynamic relationship between the top 1% income share (used to measure income inequality/distribution) and other economic variables such as multi-factor productivity, trade openness, financial development, and government spending. The estimations of panel VAR are conducted (see Section 4).

This study postulates that all variables are endogenous and that only past values affect the system in panel VARs because the modeling of panel VAR requires these limitations.

Section 2 provides a review of the relevant literature. Section 2 presents definitions and sources of the variable and brief methodologies. Section 4 details the econometrics approach and reports the study's main findings. These findings exemplify the dynamic interaction between relative income shares and other economic variables. The dynamics show that the increases in the growth rate of multi-factor productivity positively impact the increases in the top 1% income share and worsen the income inequality.

2 Studies on the Relationship between Income Inequality and Other Economic Variables

This paper focuses on the relationship between top 1% income share and multi-factor productivity and uses other economic variables as control variables. This section reviews papers on the interaction between income inequality and multi-factor productivity, financial development, government spending, or trade openness in previous literature.

2.1 Multi-Factor Productivity and Technogical Change

According to Seo and Lee (2006), [34], information and communication technology investments are positively related to productivity growth in OECD countries but not in non-OECD countries, and developed countries have advantages over developing countries concerning the progress of digitalization. They analyzed cross-sectional and time-series data from 38 countries covering 1992 to 1996.

Few articles focus on the relationship between multi-factor productivity and income inequality directly. Fortunately, there is much literature on skill-biased technological change (SBTC) and wage inequality. We review the literature between SBTC and wage inequality in three parts: empirics, theory, and both.

This paragraph is the empirical part. Card and DiNardo (2002)[8] find that the evidence linking wage inequality to SBTC is surprisingly weak. A primary candidate of an explanation for the rise in inequality in the United States is the fall in the real value of the minimum wage, leading to a steep decline in the influence of the minimum wage in the low-wage labor market. Berman et al. (1998)[3] claim that SBTC was pervasive over the 1980s and 1990s, coinciding in most, if not all, developed countries. They show that the factor content of SBTC in manufacturing alone implies a decrease in the proportion of less-skilled (production) workers, about eight times that attributable to increased trade. Then their calculation suggests that the effects of SBTC on relative wages are an order of magnitude larger than those of increased trade with the developing world, assuming that demand elasticities are approximately the same for imports and domestic production.

In theory, Galor & Moav (2000)[15] develop a growth model with the endogenous determination of both technological change and the composition of the labor force in which ability-biased technological transition generates patterns of wage inequality that are consistent with those observed in the United States and other advanced countries.

In theory and empirics, Krusell et al. (2000)[23] evaluate how much capital-skill complementarity has affected the skill premium in the postwar period. They first modify the standard two-factor (capital and labor) aggregate production that distinguishes among capital equipment, capital structures, skilled labor, and unskilled labor. This allows for different elasticities of substitution among the factors. Using U.S. time-series data, they find that the key substitution elasticities are consistent with capital-skill complementarity and very similar to microeconomics' estimates. Their main finding is that with empirically plausible differences in substitution elasticities, observed factor inputs can account for most of the variation in the skill premium. They also find that their four-factor production preserves the success of the standard neoclassical two–actor output: it too is consistent with the behavior of income shares and the returns on physical capital over time. Then, they suggest that the key to narrowing inequality is better education and training for unskilled workers because unskilled labor is competing with persistently cheaper and better capital equipment. By improving skills, workers can use new equipment and raise their productivity, rather than be replaced by new machines.

2.2 Financial Development

In Kappel (2010)[22], both cross-country and panel regression results show that inequality and poverty are reduced not only through enhanced loan markets but also through better-developed stock markets. Then, in his analysis, the effect of financial development becomes relatively weak, particularly for developing countries, and government spending only reduces income inequality in high-income countries.

According to Ghossoub & Reed (2017)[16], there is strong evidence that stock markets contribute to income inequality. Moreover, there is also evidence that public debt also contributes to inequality. Their results indicate that financial development might contribute to income inequality more than monetary policy. Furthermore, the results suggest that stock market capitalization may significantly impact inequality across countries.

2.3 Government Spending

Pontusson et al. (2002)[32] claim that strong unions, centralized wage bargaining, a large public sector, and left government have muted and sometimes overcome inegalitarian tendencies in pooled cross-section time-series analysis of wage inequality in sixteen OECD countries from 1973 to 1995.

Calderón et al. (2005)[7] find that the importance of government employment improves wage distribution.

2.4 Trade Openness

Cragg & Epelbaum (1996)[10] inform the Mexican wage debate by providing explanations for the skill-biased shift in wages, using household-level data to examine how wage and employment changes differed across industries and occupations during the reform period.

They found that the return to occupation explains close to half of the growing wage dispersion. Workers in the highest-paid occupations have experienced the most significant wage growth. Similar to other transition economies, the supply of managers and professionals is restricted precisely when their skills are most required. Further evidence of the importance of labor supply elasticities in equilibrium wage outcomes is that low-skill occupations, such as service workers, salespeople, and transport workers, experienced rapid employment growth but sluggish wage growth. Rising wages in occupations requiring more sophisticated, task-specific skills indicate that the demand for skills in Mexico has rapidly increased.

They were surprised to find that industry effects had little explanatory power, accounted for little of the rising wage dispersion, and showed only weak patterns across industries with common characteristics. This suggests that reform-induced rent dissipation is a less important source of wage change than the overall demand growth for general and occupation-specific skills. Still, some of the industry patterns are interesting. Low-skill workers have small but stable industry premia, suggesting the importance of compensating differentials for industry conditions. In contrast, high-skill workers showed significant wage and employment growth variations across industries. They also found that Mexico experienced general skill intensification in the nontraded services and traded manufacturing sectors. While high-skill employment grew at the same rate for both sectors, low-skill employment grew much more slowly in the traded sector.

Borjas et al. (1997)[5] find that the main adverse effect of immigration and trade on U.S. native outcomes falls on workers with less than high school education. Then the combined effects of immigration and trade may explain half of the decline in the relative wages of high school dropouts in the 1980s and 1990s.

Meschi & Vivarelli (2009)[26] find that only trade with high-income countries worsens income distribution in developing countries, through both imports and exports. However, it is found that intra–developing countries' trade does not decline.

Autor et al. (2013)[13] find that exposure to Chinese import competition affects local markets not just through manufacturing employment, which unsurprisingly is adversely affected, but also along numerous other margins. Import shocks trigger a decline in wages primarily observed outside of the manufacturing sector, and reductions in employment and wage levels lead to a steep drop in the average earnings of households.

Dauth et al. (2014)[12] analyze the causal impact of the rise of China and Eastern Europe on the performance of local labor markets in Germany during the period 1988 to 2008, utilizing an instrumental variable approach by Autor et al. (2013)[13]. They find that the rise in trade exposure has led to substantial gains in the German economy; however, trade again produces winners and losers since workers in import-competing industries indeed face an increased risk of job churning and lower overall employment spells.

The main finding of Roser & Cuaresma (2016)[33]'s empirical analysis is that low-wage imports to developed countries tend to worsen income inequality. This finding is very robust, and the variation in the trade variable explains a large fraction of the within-country variation in the trade variable explains a large fraction of the within-country variation of income inequality. As opposed to most other contributions to the literature, their analysis validates the Stolper-Samuelson theorem as a corollary of the Heckscher-Ohlin model; thus, their study confirms the standard prediction of trade theory.

3 Data and Methodology

3.1 Data

The source of income share data is `https://wid.world`. *Multi-Factor Productivity* is from OECD (2021), Multifactor productivity (indicator). doi: 10.1787/a40c5025-en (Accessed on 12 November 2021). *Financial development* is defined as the sum of the total deposit of the financial system and the stock market capitalization in GDP. *Government spending* is defined as the government expenditure in GDP. *Trade openness* is also defined as the sum of imports and export in GDP. The total deposit of the financial system in GDP, the stock market capitalization in GDP, the government expenditure in GDP, and the sum of imports and export in GDP are all from World Bank Open Data (`https://data.worldbank.org`). The list of countries is Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece,

Tab. 1: Variables

Variable	Definition	Source
$findev$	the sum of the total deposit of the financial system and the stock market capitalization in GDP (%)	World Bank
$govspend$	the government expenditure in GDP (%)	World Bank
MFP	multi-factor productivity (100 in 2015 in all countries)	OECD
$p99p100$	the top 1% income share	World Inequality Database
$trade$	the sum of import and export in GDP (%)	World Bank
$\_growth$ or $\_g$	the suffix standing for the growth rate of the variable	

Ireland, Israel, Italy, Japan, Korea, Luxembourg, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, Switzerland, USA. We show the histograms of variables (Fig.1). These histograms in Fig.1 show that the distributions of the growth rates of variables are nearer normal than the distributions of the levels of variables. This is one reason why the growth rates are preferable to the levels. However, the growth rates of variables have fat tails compared to the normal distribution.

3.2 Methodology

3.2.1 Panel Specification Test

The first generation of the panel unit root test is different from the second generation of that in the viewpoint of the cross-sectional dependence. There are several types of nonstationary tests used in panel data. We apply the first generation of the panel unit root test to the unbalanced panel data. The methods are Levin, Lin & Chu (2002)[24], Breitung (2001)[6], Im, Pesaran & Shin (2003)[19], Augmented Dickey-Fuller based on Maddala & Wu (1999)[25] and PP based on Choi (2001)[9]. All tests include the time trends and the intercepts. Then, the Cross-sectional Dependence (CD) tests (Pesaran (2015)[29], and Pesaran (2021)[30]) justify panel regression models and panel vector autoregression models as follows because the CD tests cannot reject the null hypothesis of the cross-sectional independence.

3.2.2 Panel Regression

Dynamic panel regression has developed since the finding of Nickell (1981)[27] bias. Arellano & Bond (1991)[1] overcome Nickell bias, introducing the generalized methods of moments (GMM) estimators popularized by Hansen (1982)[18]. However, their estimation has a large bias when the coefficient of the lag of the dependent variable is near one. In other words, the dependent variable has a unit root. With additional moment conditions, Blundell & Bond (1998)[4] develop the system GMM estimator to deal with this bias. However, these arguments focused on single equation dynamic panel data models. The static panel regressions, aka the fixed-effects and random-effects least square dummy variables and ordinary least squares, are also estimated.

3.2.3 Panel Granger Causality Test

Granger (1969)[17] explored the relationships between certain classes of econometric models involving feedback and the functions arising in spectral analysis. In the two-variable case, the feedback mechanism can be broken down into two causal relations. The cross–pectrum can be considered the sum of two cross spectra, each closely connected with one of the causations.

Dumitrescu & Hurlin (2012)[14] propose a simple Granger (1969)[17] non-causality test for heterogeneous panel data models. Under the null hypothesis of homogeneous non-Causality, there is no causal

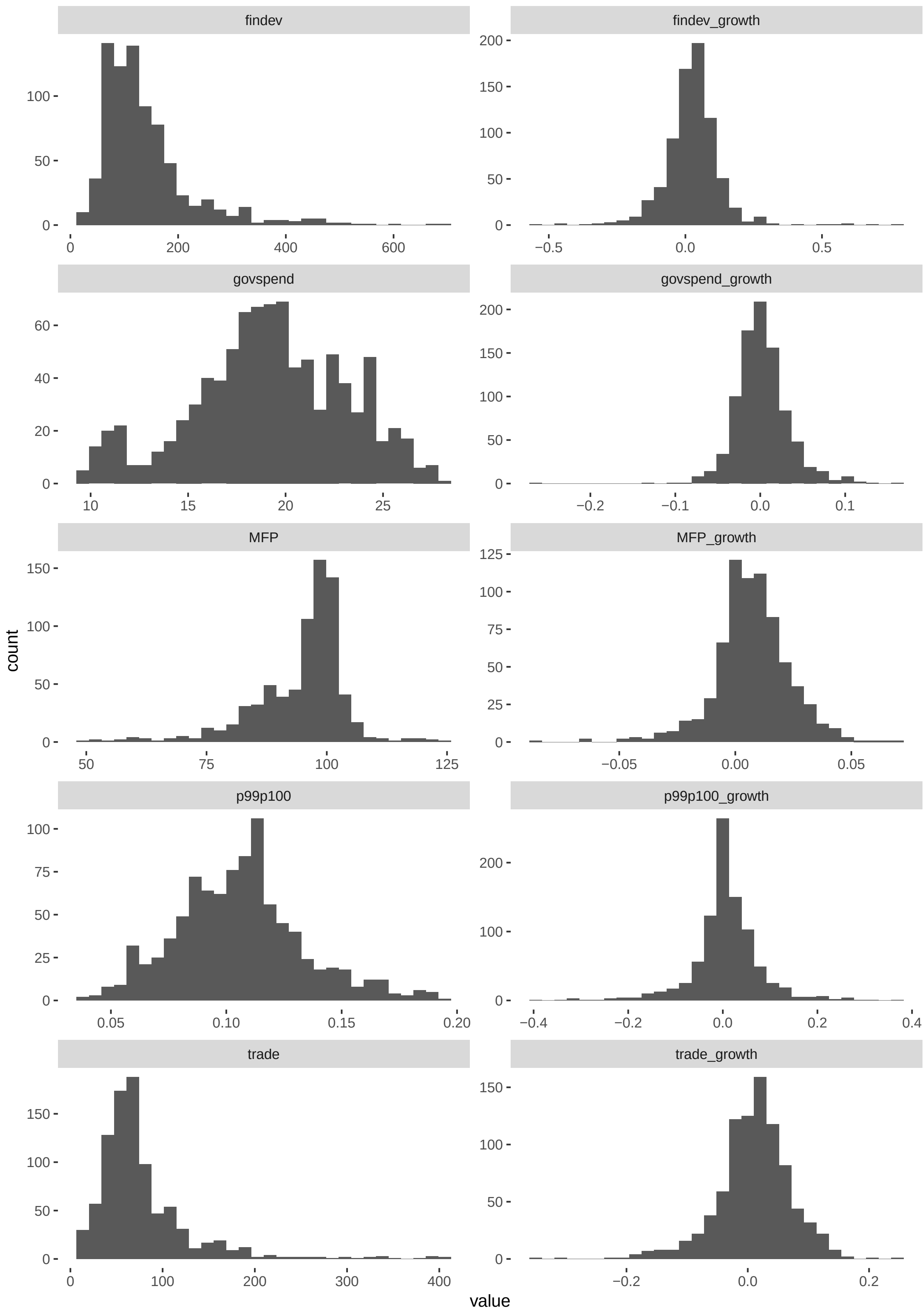

Fig. 1: Histograms

relationship for any of the cross-section units of the panel. Under the alternative, there are two subgroups of cross-section units: one characterized by causal relationships from x to y (even though the regression model is not necessarily the same) and another subgroup for which there is no causal relationship from x to y. There are four main advantages. First, the standardized, average Walds statistics are simple to compute and have a normal asymptotic distribution. Second, the original paper's Monte Carlo simulations show that its panel statistics lead to a substantial increase in the power of the Granger non-causality tests even for samples with very small T and N dimensions. Third, its test statistics (based on a cross-section average of individual Wald statistics) do not require any particular panel estimation. Finally, the test can be easily implemented in unbalanced panels or panels with different lag orders K for each individual.

3.2.4 Panel Vector Autoregression

Sigmund & Ferstl (2019)[35] extend two general methods of moment (GMM) estimators to panel vector autoregression (PVAR) models with p lags of endogenous variables, predetermined and exogenous variables. They first extend the first difference GMM estimator and the system GMM estimator to this extended PVAR model.

The PVAR model has the impulse response function as the vector autoregression in time series analysis. There are two popular impulse response functions: the orthogonalized impulse response function (OIRF) and the generalized impulse response function (GIRF). The orderings of the dependent variables affect the results of the OIRF; however, these orderings have no impact on the GIRF analysis.

This study estimates the simple PVAR model as follows:

$$\mathbf{y}_{i,t} = \sum_{l=1}^{p} \mathbf{\Phi}_l \mathbf{y}_{i,t-l} + \mu_i + \epsilon_{i,t}, i = 1, 2, \ldots, N, t = 1, 2, \ldots, T \tag{1}$$

where m is the number of jointly determined dependent variables, N is the number of the cross-section dimension, T is the number of time series the dimension, $\mathbf{y}_{i,t} = (y_{1,i,t}, y_{2,i,t}, \ldots, y_{m,i,t})'$ is $m \times 1$ vector of jointly determined dependent variables, and $\{\mathbf{\Phi}_i, i = 1, 2, \ldots, p\}$ are $m \times m$ coefficient matrices.

Pesaran & Shin (1998)[28] choose to shock only one element, say its rth element, and integrate out the effects of other shocks using the historically observed distribution of the errors. In this case, we have

$$GIRF(k, r, \mathbf{\Sigma}_\epsilon) = \mathbb{E}[\mathbf{y}_{i,t+k} | \epsilon_{i,t,r} = \delta_r, \mathbf{\Sigma}_\epsilon] - \mathbb{E}[\mathbf{y}_{i,t+k} | \mathbf{\Sigma}_\epsilon] \tag{2}$$

By Setting $\delta_r = \sqrt{\mathbf{\Sigma}_{\epsilon,r,r}}$, we obtain the generalized impulse response function by

$$GIRF(k, r, \mathbf{\Sigma}_\epsilon) = \mathbf{A}_k \mathbf{\Sigma}_\epsilon (\boldsymbol{\sigma}_{r,r})^{-1/2} \tag{3}$$

where $\boldsymbol{\sigma}_{r,r}$ is the rth diagonal element of $\mathbf{\Sigma}_\epsilon$ and the $m \times m$ coefficient matrices $\mathbf{A}_l$ can be obtained using the following recursive relations:

$$\mathbf{A}_l = \mathbf{\Phi}_1 \mathbf{A}_{l-1} + \mathbf{\Phi}_2 \mathbf{A}_{l-2} + \cdots + \mathbf{\Phi}_p \mathbf{A}_{l-p}, l = 1, 2, \ldots, \tag{4}$$

with $\mathbf{A}_0 = \mathbf{I}_m$ ($m \times m$ identity matrix) and $\mathbf{A}_l = 0$ for $l < 0$.

4 Econometric Analysis

4.1 Panel Specification Test

Section 4.1 explores the property of the panel data in this study. Section 4.1.1 tests the existence of panel unit root in each variable. Then, Section 4.1.2 checks the assumption of cross-sectional independence.

Tab. 2: Panel Unit Root Test on $\log(p99p100)$

Method	Statistic	Prob.	N	Obs
Levin, Lin & Chu t*	0.38129	0.6485	23	846
Breitung t-stat	-3.91411	0.0000	23	823
Im, Pesaran and Shin W-stat	-0.8434	0.2004	23	846
ADF - Fisher Chi-square	66.4119	0.0260	23	846
PP - Fisher Chi-square	45.1714	0.5059	23	897

Tab. 3: Panel Unit Root Test on $p99p100\_g$

Method	Statistic	Prob.	N	Obs
Levin, Lin & Chu t*	-16.1750	0.0000	23	828
Breitung t-stat	-9.38374	0.0000	23	805
Im, Pesaran and Shin W-stat	-17.5582	0.0000	23	828
ADF - Fisher Chi-square	388.718	0.0000	23	828
PP - Fisher Chi-square	1295.75	0.0000	23	874

4.1.1 Panel Unit Root Test

There is no package applied to the unbalanced panel data for panel unit root tests in R. We use Eviews 11 to test the nonstationarity of the unbalanced panel data. The null hypothesis of these tests is a common unit root process for Levin, Lin & Chu (2002)[24] and Breitung (2001)[6]. In null hypotheses, Im, Pesaran & Shin (2003)[19], Augmented Dickey-Fuller based on Maddala & Wu (1999)[25] and PP based on Choi (2001)[9] assume that the individual unit root process exists. Because the log level of each variable has a mixed result, tests cannot reject the nonstationarity. However, the growth rate of each variable shows the stationarity in each test.

4.1.2 Cross-sectional Dependence Test

We test the cross-sectional dependence in panels (Pesaran (2015)[29] and Pesaran (2021)[30]) to justify panel regressions and panel vector autoregressions (PVAR) as follows. The null hypothesis is that cross-sectional independence exists. The acceptances of the null in Model 3, Model 7, and Model 8 are essential because the models of panel regressions and PVAR postulate cross-sectional independence.

Model 1:

$$\log(p99p100) \sim 1 \tag{5}$$

Tab. 4: Panel Unit Root Test on $\log(findev)$

Method	Statistic	Prob.	N	Obs
Levin, Lin & Chu t*	2.05385	0.9800	23	680
Breitung t-stat	-0.67230	0.2507	23	657
Im, Pesaran and Shin W-stat	-0.51422	0.3035	23	680
ADF - Fisher Chi-square	54.4230	0.1845	23	680
PP - Fisher Chi-square	68.2787	0.0181	23	759

Tab. 5: Panel Unit Root Test on $findev\_g$

Method	Statistic	Prob.	N	Obs
Levin, Lin & Chu t*	-7.62923	0.0000	23	664
Breitung t-stat	-5.40448	0.0000	23	641
Im, Pesaran and Shin W-stat	-11.1748	0.0000	23	664
ADF - Fisher Chi-square	209.502	0.0000	23	664
PP - Fisher Chi-square	279.195	0.0000	23	728

Tab. 6: Panel Unit Root Test on $\log(govspend)$

Method	Statistic	Prob.	N	Obs
Levin, Lin & Chu t*	-0.63211	0.2637	23	832
Breitung t-stat	-0.44489	0.3282	23	809
Im, Pesaran and Shin W-stat	-1.87622	0.0303	23	832
ADF - Fisher Chi-square	68.1486	0.0186	23	832
PP - Fisher Chi-square	35.9393	0.8568	23	882

Tab. 7: Panel Unit Root Test on $govspend\_g$

Method	Statistic	Prob.	N	Obs
Levin, Lin & Chu t*	-13.7490	0.0000	23	815
Breitung t-stat	-12.0659	0.0000	23	792
Im, Pesaran and Shin W-stat	-14.1224	0.0000	23	815
ADF - Fisher Chi-square	275.326	0.0000	23	815
PP - Fisher Chi-square	552.375	0.0000	23	859

Tab. 8: Panel Unit Root Test on $\log(MFP)$

Method	Statistic	Prob.	N	Obs
Levin, Lin & Chu t*	-3.90954	0.0000	23	672
Breitung t-stat	1.27848	0.8995	23	649
Im, Pesaran and Shin W-stat	-2.14014	0.0162	23	672
ADF - Fisher Chi-square	76.3204	0.0033	23	672
PP - Fisher Chi-square	57.4062	0.1207	23	715

Tab. 9: Panel Unit Root Test on MFP_g

Method	Statistic	Prob.	N	Obs
Levin, Lin & Chu t*	-12.5293	0.0000	23	671
Breitung t-stat	-10.7396	0.0000	23	648
Im, Pesaran and Shin W-stat	-12.7406	0.0000	23	671
ADF - Fisher Chi-square	232.559	0.0000	23	671
PP - Fisher Chi-square	447.537	0.0000	23	692

Tab. 10: Panel Unit Root Test on $\log(trade)$

Method	Statistic	Prob.	N	Obs
Levin, Lin & Chu t*	-3.46823	0.0003	23	854
Breitung t-stat	-4.13334	0.0000	23	831
Im, Pesaran and Shin W-stat	-2.84178	0.0022	23	854
ADF - Fisher Chi-square	68.7635	0.0164	23	854
PP - Fisher Chi-square	47.6360	0.4139	23	882

Tab. 11: Panel Unit Root Test on $trade\_g$

Method	Statistic	Prob.	N	Obs
Levin, Lin & Chu t*	-19.5763	0.0000	23	835
Breitung t-stat	-17.3235	0.0000	23	812
Im, Pesaran and Shin W-stat	-17.5588	0.0000	23	835
ADF - Fisher Chi-square	335.193	0.0000	23	835
PP - Fisher Chi-square	882.426	0.0000	23	859

Model 2:

$$\log(p99p100) \sim lag(\log(p99p100), 1) \tag{6}$$

Model 3:

$$\log(p99p100) \sim \log(findev) + \log(govspend) + \log(MFP) + \log(trade) \tag{7}$$

Model 4:

$$\log(p99p100) \sim lag(\log(p99p199), 1) + \log(findev) + \log(govspend) + \log(MFP) + \log(trade) \tag{8}$$

Model 5:

$$p99p100\_g \sim 1 \tag{9}$$

Model 6:

$$p99p100\_g \sim lag(p99p100\_g, 1) \tag{10}$$

Model 7:

$$p99p100\_g \sim findev\_g + govspend\_g + MFP\_g + trade\_g \tag{11}$$

Model 8:

$$p99p100\_g \sim lag(p99p100\_g, 1) + findev\_g + govspend\_g + MFP\_g + trade\_g \tag{12}$$

Tab. 12: Pesaran CD test for cross-sectional dependence in panels

	Model 1	Model 2	Model 3	Model 4
p-value	< 2.2e-16	< 2.2e-16	0.5818	0.001172
	Model 5	Model 6	Model 7	Model 8
p-value	< 2.2e-16	< 2.2e-16	0.8016	0.8176

Tab. 13: Panel Regression Results (Log Level)
$N = 23$, $T = 19 - 33$, $Obs = 643$

	GMM(AB)	GMM(BB)	LSDV-FE	LSDV-RE	OLS
$intercept$	-	-	-	-5.907368 (0.662111) ***	-4.668240 (0.988862) ***
$lag(\log(p99p100), 1)$	0.641355 (0.052520) ***	0.9107513 (0.0198344) ***	-	-	-
$\log(findev)$	0.056418 (0.026703) **	0.0126924 (0.0073970) *	0.104204 (0.058388) *	0.113176 (0.053222) **	0.167354 (0.079401) **
$\log(govspend)$	-0.296568 (0.070712) ***	-0.0239185 (0.0192916) -	-0.601121 (0.135123) ***	-0.561398 (0.130038) ***	-0.206058 (0.204723) -
$\log(MFP)$	0.227112 (0.117784) *	-0.0339899 (0.0160204) **	0.990367 (0.212212) ***	0.991965 (0.213463) ***	0.579963 (0.325578) *
$\log(trade)$	0.083366 (0.040065) **	-0.0072020 (0.0072473) -	0.089698 (0.094406) -	0.056818 (0.082888) -	-0.105420 (0.074719) -
$Adj.R^2$	-	-	0.50196	0.50818	0.25677

The cluster-robust standard errors are in the parentheses. ***, **, * denote p-values at the 1%, 5%, 10%, level of significance, respectively.

4.2 Panel Regression

We, at first, estimate the panel regression based on the single equation model to understand the relationship between $p99p100$ and other variables ($findev$, $govspend$, MFP and $trade$) because the cross-sectional dependence tests in Section 4.1.2 favor the models as follows. First model has $\log(p99p100)$ as the dependent variable and $\log(findev)$, $\log(govspend)$, $\log(MFP)$ and $\log(trade)$ as explanatory variables. Second model has $p99p100\_g$ as the dependent variable and $findev\_g$, $govspend\_g$, MFP_g and $trade\_g$ as the explanatory variables. Third model has the variables in second model and $lag(p99p100\_g, 1)$ as the added explanatory variable. Ignoring the nonstationarity, we estimate the relationship between the logarithms of economic variables in Tab.13. Because we cannot rule out the panel unit roots in the dependent and explanatory variables in Section 4.1, we use the log-based growth rate of each variable ($growth\_rate_t := \log(value_t) - \log(value_{t-1})$). We present the four types of the panel regression; Arellano & Bond (1991)[1] GMM estimator (AB), Blundell & Bond (1998)[4] system GMM estimator (BB), the fixed-effect estimator of the least square dummy variable (LSDV-FE), the random-effect estimator of the least squares dummy variable (LSDV-RE) and the ordinary least square estimator (OLS). All results here have similar coefficients and cluster-robust standard errors (Tab.14). Financial developments and multi-factor productivities positively impact the top 1% income share, and governmental spendings negatively affect the top 1% income share. Finally, trade openness does not have a statistically significant relationship with the top 1% income share.

Tab. 14: Panel Regression Results (Growth Rate)

$N = 23$, $T = 18 - 32$, $Obs = 613$

	GMM(AB)	GMM(BB)	LSDV-FE	LSDV-RE	OLS
				0.00062332	0.00062332
$intercept$	-	-	-	(0.00284872)	(0.00251719)
				-	-
	-0.096297	-0.084107			
$lag(p99p100\_g, 1)$	(0.063690)	(0.063488)	-	-	-
	-	-			
	0.123438	0.126586	0.120760	0.12223124	0.12223124
$findev\_g$	(0.036566)	(0.035943)	(0.036712)	(0.03757021)	(0.03707941)
	***	***	***	***	***
	-0.681336	-0.649749	-0.592580	-0.60060573	-0.60060573
$govspend\_g$	(0.164601)	(0.146381)	(0.170290)	(0.14805137)	(0.16241092)
	***	***	***	***	***
	1.067471	1.045292	1.015784	0.95643111	0.95643111
MFP_g	(0.220776)	(0.185884)	(0.221087)	(0.21385474)	(0.19648973)
	***	***	***	***	***
	0.039275	0.050342	0.056217	0.05589000	0.05589000
$trade\_g$	(0.051375)	(0.046292)	(0.048856)	(0.04594620)	(0.04779425)
	-	-	-	-	-
$Adj.R^2$	-	-	0.16794	0.19677	0.19677

The cluster-robust standard errors are in the parentheses. ***, **, * denote p-values at the 1%, 5%, 10%, level of significance, respectively.

Tab. 15: Panel Granger Causality Results (Log Level)

	$\log(p99p100)$	$\log(findev)$	$\log(govspend)$	$\log(MFP)$	$\log(trade)$
$\log(p99p100)(-1)$	-	2.3051 (0.02116) **	3.1687 (0.001531) ***	1.6182 (0.1056) -	3.1606 (0.001574) ***
$\log(findev)(-1)$	4.0018 (6.287e-05) ***	-	2.9834 (0.00285) ***	3.4402 (0.0005812) ***	2.7966 (0.005165) ***
$\log(govspend)(-1)$	5.8093 (6.273e-09) ***	2.9162 (0.003543) ***	-	2.5783 (0.009927) ***	8.7705 (< 2.2e-16) ***
$\log(MFP)(-1)$	8.5116 (< 2.2e-16) ***	5.0405 (4.642e-07) ***	3.1442 (0.001666) ***	-	9.2043 (< 2.2e-16) ***
$\log(trade)(-1)$	2.1781 (0.0294) **	2.623 (0.008715) ***	1.7326 (0.08317) *	1.6287 (0.1034) -	-

The p-values are in the parentheses. ***, **, * denote rejection of null hypothesis at the 1%, 5%, 10%, level of significance, respectively.
(-1) stands for the consideration of the one-lag in panel Granger Causality test.

4.3 Panel Granger Causality Test

Panel Granger Causality test (Dumitrescu & Hurlin (2012)[14]) is the extension of Granger causality in time series analysis (Granger (1969)[17]) to panel data. The null hypothesis of this test is that the non-existence of the Granger causality is for all individuals, and the alternative is that at least one individual has the Granger causality. Because most models reject the non-Granger causality, these results validate the panel vector autoregression (PVAR) model as follows (section 4.4). The PVAR model postulates that some lags in the dependent variables determine the current dependent variables.

4.4 Generalzed Impulse Response Functions of Panel Vector Autoregression

Fig.2 is the estimation result of the generalized impulse response functions (GIRF) in the two-lag panel vector autoregression (PVAR) model based on the log level of the variables in Tab.1 over 20 years. Fig.3 is also the estimation result of GIRFs in the two-lag PVAR model based on the growth rate of the variables in Tab.1 over ten years.

Fig.2 and Fig.3 show movements of all economic variables have similar directions in the same two-lag model of the PVAR. However, Fig.2 indicates the log-level PVAR model has wider 95% bootstrap confidence intervals than the growth rate PVAR model in Fig.3. Fig.3 has more precise estimation results than Fig.2 to forecast the dynamic impact of each economic variable. This result shows that we still need to consider the panel nonstationarity in the PVAR.

Fig.2 and Fig.3 are the estimation results of generalized impulse response functions in the PVAR mode with the two lags. These results match the results of panel regression (Tab.14). The impacts on $p99p100\_g$ of $findev\_g$, MFP_g are positive, the impact of $govspend\_g$ is negative, and the impact of $trade\_g$ is still unclear.

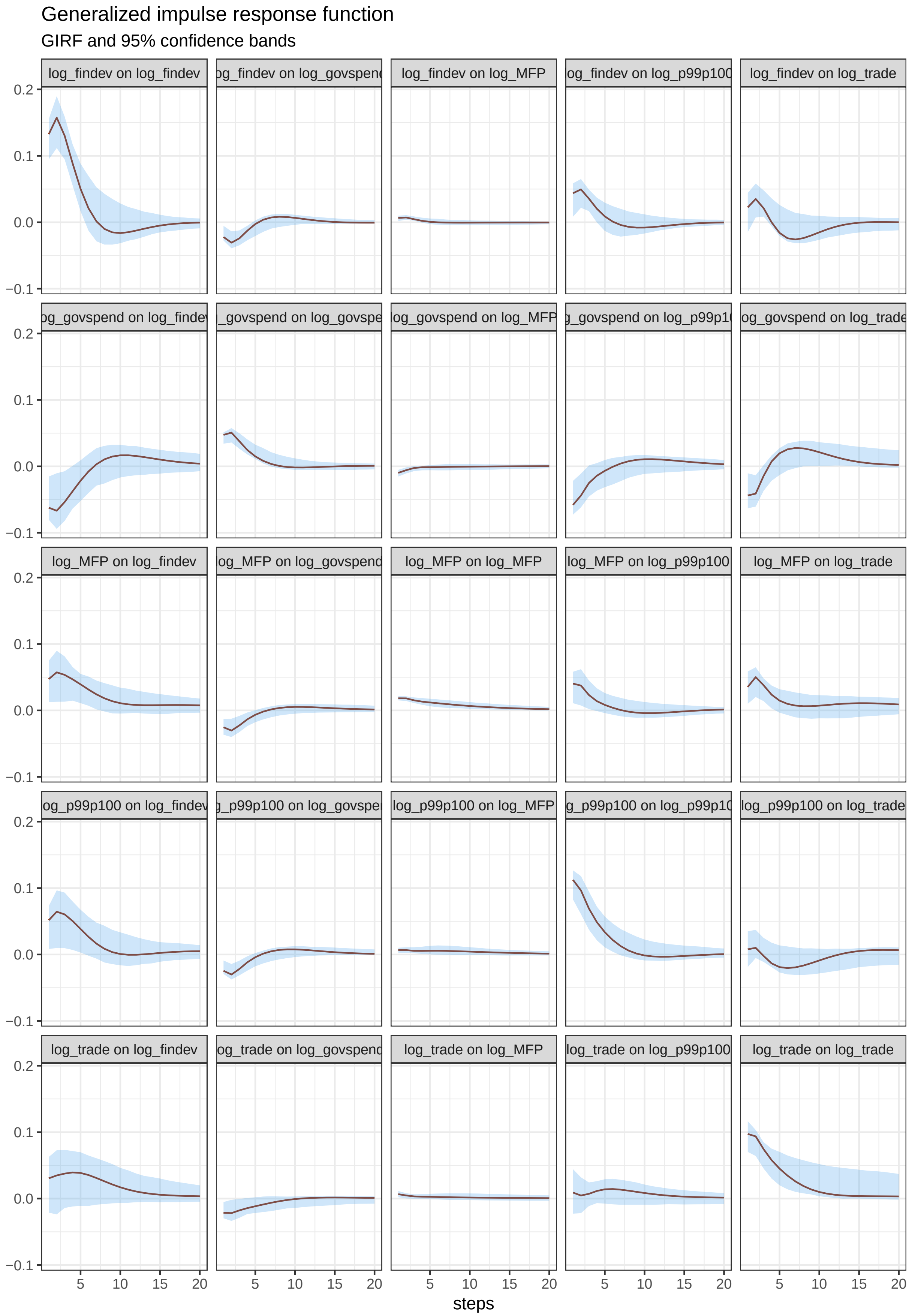

Fig. 2: Generalized Impulse Response Analysis of Panel Vector Autoregression (Log Level)

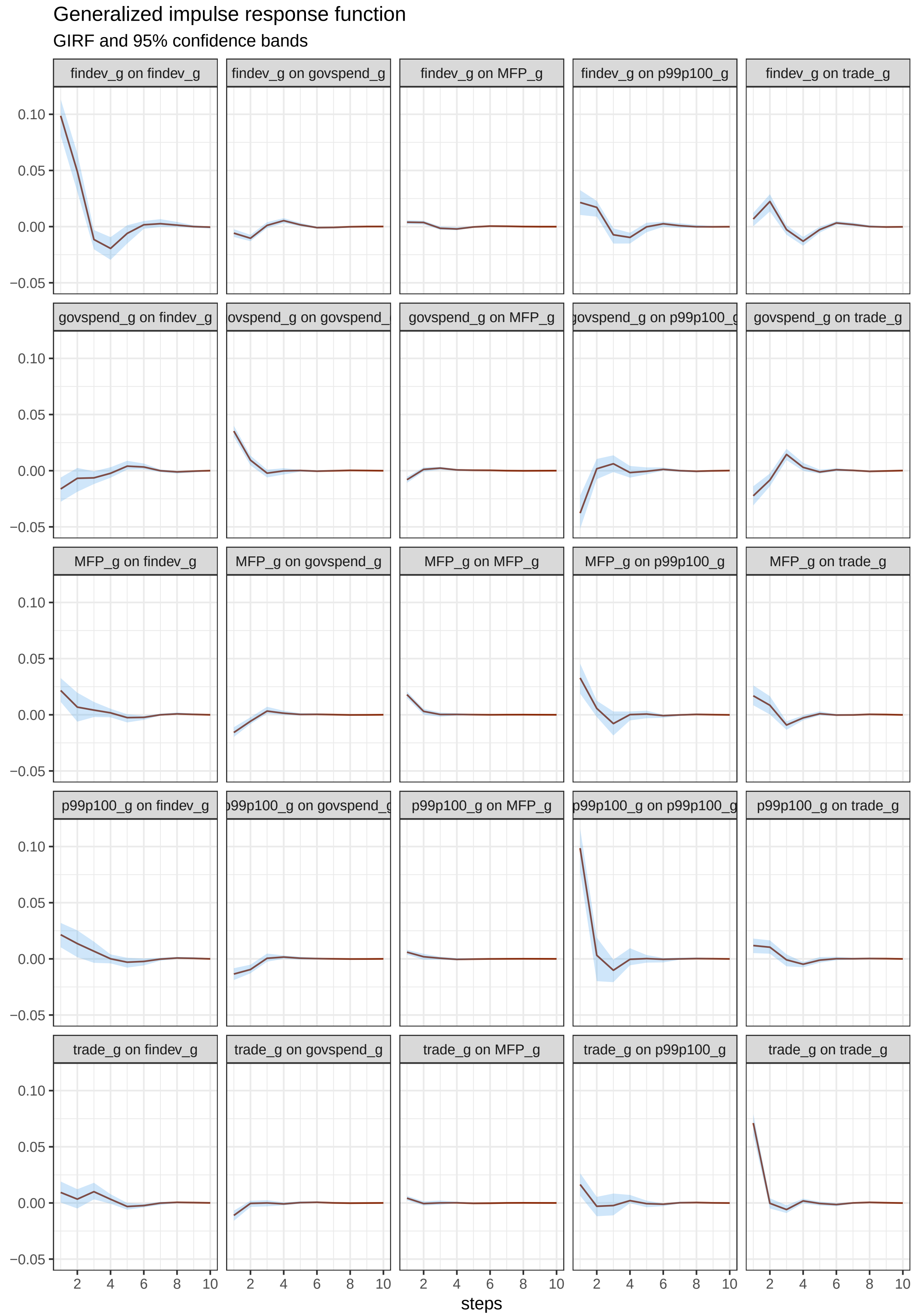

Fig. 3: Generalized Impulse Response Analysis of Panel Vector Autoregression (Growth Rate)

Tab. 16: Panel Granger Causality Results (Growth Rate)

	$p99p100\_g$	$findev\_g$	$govspend\_g$	MFP_g	$trade\_g$
$p99p100\_g(-1)$	-	0.43688 (0.6622) -	6.1331 (8.618e-10) ***	1.1375 (0.2553) -	2.6943 (0.007053) ***
$findev\_g(-1)$	4.0556 (5e-05) ***	-	7.2815 (3.302e-13) ***	2.0844 (0.03713) **	2.339 (0.01934) **
$govspend\_g(-1)$	2.9132 (0.003578) ***	-1.0386 (0.299) -	-	3.4668 (0.0005266) ***	-1.5811 (0.1138) -
$MFP\_g(-1)$	2.3227 (0.02019) **	0.26927 (0.7877) -	1.3853 (0.166) -	-	3.1069 (0.00189) ***
$trade\_g(-1)$	0.54106 (0.5885) -	2.6883 (0.007181) ***	-0.026885 (0.9786) -	5.8272 (5.636e-09) ***	-

The p-values are in the parentheses. ***, **, * denote rejection of null hypothesis at the 1%, 5%, 10%, level of significance, respectively
(-1) stands for the consideration of the one-lag in panel Granger Causality test.

5 Conclusion

Panel regressions in Section 4.2 ignore the dynamics, and the impulse response function analysis of the panel vector autoregressions (PVAR) in Section 4.4 neglects the effects of variables at the same time. However, panel regressions in Section 4.2 and the PVAR model in Section 4.4 have the same result that the growth of the multi-factor productivity increases the growth of the top 1% income share. Then, trade openness has no statistically significant effects on the top 1% income share, financial developments have a positive impact on the top 1% income share, and government spendings affect the top 1% income share negatively in Section 4.2 and 4.4.

Compliance with Ethical Standards

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Conflict of interest

The author has no conflicts of interest to declare.

Ethical approval

This article does not contain any studies with human participants performed by any authors.

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