The Empirical Economics of Inequality

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(Degree)
博士（経済学）

(Date of Degree)
2021-03-25

(Date of Publication)
2024-03-25

(Resource Type)
doctoral thesis

(Report Number)
甲第7986号

(URL)
https://hdl.handle.net/20.500.14094/D1007986

博士論文

令和２年１２月

神戸大学大学院経済学研究科

経済学専攻

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（格差の実証経済学）

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Executive Summary

Economic inequality is one of the most challenging problems today. The United Nations adopted the Sustainable Development Goals (SDGs) to end absolute poverty in 2015. Economic inequality is different from poverty in the definition. However, economic inequality has intricated relationships with poverty.

The economic inequality measure is readily available, so Chapter 2 has the basis of income bracket.

Chapter 3 dedicates the relationship between total fertility rates (TFRs) and the economic inequality measure, such as Gini index on each prefecture and between TFRs and the demographic change.

Chapter 4 takes notes on the relationship between crime rates and the same Gini index data as Chapter 3.

Acknowledgments

First and foremost, I want to express my appreciation to my supervisor, Prof. Takashi Kamihigashi. He gives me great advice and precious navigation of research.

Second, I must appreciate to Prof. Naoya Sueishi. He took lectures on me on a one-to-one basis and also the excellent advice.

In the end, I should express my appreciation to my family.

Kobe, 10 December 2020
Yosuke Sasaki

Contents

List of Tables

List of Figures

Chapter 1

Introdution

1.1 The Background of the Study

As before, the United Nations adopted the Sustainable Development Goals (SDGs) in 2015. To end absolute poverty is the main objective of SDGs. The research on poverty has an intricate relationship with economic inequality. However, microdata required to research poverty is few in Japan. Instead, the Bureau of Statistics offered microdata available to research economic inequality. Economic inequality is the most challenging problem the world faces now. Total fertility rates (TFRs) are weighty matters from the 20th century. Developing countries have high TFRs enough to lead to the explosion of the population. Some developed countries (e.g., Japan and South Korea) face low TFRs to destroy their economies and societies. This thesis focuses on low TFRs. Japan's low TFRs and its declining population have become a severe issue. The decreasing number of birth in Japan accelerates unanticipatedly. The low TFRs decline population and give rise to the aging society. The problems are listed as follows; the decrease of labor supply, the shrinkage of market size, the decline of economic growth rate, the devastation of region and society, the increase of the burden on working generation, and the worsening of governmental service. Crime rates are a fringe issue compared with economic inequality and TFRs. However, every society tackles crime rates to save security.

The impact of trade openness on economic inequality helps democratic countries backlash globalization since the Cold War. So, the linkage between economic inequality and trade openness has a severe implication. Asteriou et al. (2014)[5] investigates the relationship between income inequality and globalization, measured with both trade and financial variables. They find disparities were observed in the financial globalization effects within a specific group or among country groups. Spilimbergo et al. (1999)[57] show that the effects of trade openness on inequality depend on factor endowments, and land and capital intensive countries have a less equal income distribution.

The interaction between economic inequality and TFRs is a fundamental problem in Japan to sustain a society because Japan has the lowest TFRs, even in developed countries. So, Japan projects to encounter the steepest declining population in the history of humanity. Few papers feature TFRs. However, there are some papers on the relationship between TFRs and other variables. Willis (1973)[60] finds that the interaction model captures an essential empirical regularity in the cross-section relationship between fertility and measures of husband's income and wife's education that has become apparent in the emergence of a

U-shaped relationship between fertility and income. Lutz et al. (2006)[38] empirically find a consistent and significant negative relationship between human fertility and population density, using fixed-effects models on the time series of 145 countries and controlling for critical social and economic variables such as GDP per capita, infant mortality, female labor force participation, and female literacy. Myrskylä et al. (2009)[46] report that TFRs in highly developed countries have inverted J-shape curves over the Human Development Index (HDI). The HDI is a summary measure of average achievement in key dimensions of human development.

Several articles debate the correlation between economic inequality and crime rates. Messner & Tardiff (1986)[44] present an analysis of the relationship between levels of economic inequality and homicide rates for a sample of 26 neighborhoods in Manhattan, New York. They report that homicide rates tend to be highest in those neighborhoods characterized by extreme poverty and pervasive marital dissolution. Patterson (1991)[49] examines the relationship between crime rates and aggregate economic conditions for 57 small social areas. His findings indicate that absolute poverty is more strongly associated with neighborhood crime rates. Fajnzylber et al. (2002)[25] investigate the robustness and causality of the link between income inequality and violent crime across countries. They conclude that an increase in income inequality has a significant and robust effect on rising crime rates. Besides, the GDP growth rate has a significant crime-reducing impact. Since the rate of growth and income distribution jointly determine poverty reduction, the two results, as mentioned above, imply that poverty alleviation has a crime-reducing effect.

1.2 The Objectives of the Study

This study aims to clarify economic inequality itself and the connection between economic inequality and its social implication. This thesis focuses on the relationship between economic inequality and trade openness, dedicating economic disparities, and other socio-economic variables such as total fertility rates (TFRs) and crime rates. Both depict essential determinants of social well-being. TFRs constitute a significant concern that Japan confronts. The relationship between crime rates and economic inequality is a severe issue.

1.3 The Structure of the Study

Chapter 2 analyzes the relationship between economic inequality and other economic variables to utilize the income bracket as the economic inequality measure. This chapter's contribution is the inverted U-shape of trade openness on the top 1% income bracket and the dynamics between trade openness and income brackets. Multiple income brackets make it possible to analyze the impact of trade openness on income brackets.

The analysis of Chapter3 is on total fertility rates (TFRs) and other socio-economic measures, such as the expenditure Gini index. The Gini index has the basis on each prefecture city and years from 1981 and 2016. The increase of the Gini index has a negatively statistical significance on the TFRs. Other prominent results are that population density has an inverted U-shape relationship with TFRs. The real expenditure (the expenditure adjusted by the consumer price index) also has an inverted U-shape with TFRs.

Chapter 4 analyzes crime rates and economic inequality and uses other socio-economic measures as control variables. These measures include the Gini index used in Chapter 3. Gini index has a positive statistical significance on the crime rates. This result is well fit in the literature.

Chapter 5 concludes this thesis.

1.4 Data Source

The author originally recalculates unpublished data such as Gini index of the expenditure, using microdata of "the Family Income and Expenditure Survey" reported by the Statistics Bureau, Ministry of Internal Affairs and Communications of Japan.

Chapter 2

The Impact of Trade Openness on Income Inequality

2.1 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 these changes have been occurring since the 1980s and were just exacerbated by the financial crisis. Because of the popularity of Piketty (2015)[50]'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 major 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)[50]), trade openness (Daumal (2013)[19]), and economic growth (Panizza (2002)[48]) using cross-country panel data or time-series analyses of a single country. However, the Gini index has shortcomings with regard to capturing inequality in the income distribution. Most importantly, Gini index data are not available for every year, which precludes any analysis that incorporates business cycles over the medium term (i.e., up to a few years). Studies such as Spilimbergo et al. (1999)[57] and Asteriou et al. (2014)[5] have estimated the relationship between income inequality and trade openness, but they neglect dynamic effects across time because of the lack of annual availability of Gini index data. Relative shares of total income has advantages over the Gini index as a measure of income inequality, in that the data are annually available and it provides an explicit depiction of the income distribution across the population. This enables comparison of the share in total income of, for example, the top 1% relative to the bottom 50% of the population. Jaumotte et al. (2013)[31] discovered that increasing trade and financial globalization had separately identifiable and opposite effects on the income distribution. Trade liberalization and export growth were found to be associated with lower income inequality, whereas increased financial openness was associated with higher inequality. However, Bergh and Nilsson (2010)[8] 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 that affect it.

The primary contributions of the extant literature include the analysis of dynamic effects (over two or more terms) between income shares and trade openness and the estimation of the relationship between inequality and trade openness using dynamic panel regression models (Arellano and Bond (1991)[3]). The possibility of an explosive increase in income inequality caused by economic policies, such as tax cuts for the rich, in the panel vector autoregression (PVAR) model has also been investigated (Sigmund and Ferstl (2019)[56]).

Building on previous studies such as these, this study estimates the relationship between the relative shares of income brackets (which is used as a measure of income inequality) and other economic variables such as trade openness, financial development, and government spending. Static and dynamic panel data analyses are conducted (see Section 2.6). The analysis is also expanded to include population and multi-factor productivity.

This study postulates that trade openness (measured as the sum of imports and exports as a percentage of gross domestic product [GDP]) has a statistically significant and adverse impact on the equality of the income distribution. Specifically, an inverted U-shaped relationship between trade openness and the relative share of the top income bracket is identified. Jauch and Watzka (2016)[30] provided a model that included the squared term of the financial development index. However, the inverted U-shaped relationship between trade openness and income inequality is a new result in the literature on income distribution . At first, income inequality rises but then this trend changes and the share of income earned by the top bracket begins to decline again. The model explains the cause of the inverted U-shaped relationship using static panel regressions. The multi-term relationship between relative income shares and trade openness is also a focus of analysis . The adverse effect of trade openness is a new finding that indicates that upper-middle-income and lower-income workers are directly and adversely affected by trade liberalization. The income share of these groups falls, relative to the income of the entire population. To estimate the impact on income shares from dynamic effects and to check the robustness of the analysis, recently developed PVAR techniques (Sigmund and Ferstl (2019)[56]) are applied to model the relationship between the top 1% of the income distribution and trade openness. Utilizing relative income shares as a measure of inequality sheds new light on the impact of trade openness on the entire income distribution over time.

Section 2.2 provides a review of the relevant literature. Section 2.3 details the econometrics approach and reports the study's main findings. In summary, models with squared terms for trade openness and financial development variables indicate that both of these economic variables can decelerate the pace of rising income inequality. This exemplifies the dynamic interaction between trade openness and relative income shares.

2.2 Studies on the Relationship between Income Inequality and Trade Openness

The panel data used in this study predominantly cover developed countries, where various aspects of free trade contribute to rising income inequality. Bergh and Nilsson (2010)[8] stated that trade liberalization and economic globalization increase income inequality. Trade openness exerts downward pressure on the wages of unskilled workers in rich countries while increasing income from capital. This results in an increase in income inequality within these economies. Because skilled labor and capital endowments in developed countries are at relatively high levels, increasing imports are expected to hurt unskilled labor (Reuveny and Li (2003)[53]). The Stolper–Samuelson theorem is unable to explain the increasing inequality in developing countries (Chiquiar (2008)[15] & Wang et al. (2009)[59]). The Stolper-Samuelson Theorem is that if countries are abundant in unskilled labor, we should have expected a decrease in their skill premiums as they opened-up to trade with more advanced economies(Chiquiar (2008)[15]). To address the gap in the knowledge on this topic, this study estimates the dynamic effects of trade openness on relative income shares using dynamic panel models by the Generalized Method of Moments.

A number of recent studies on wage inequality in developing economies have abandoned factor-price equalization, which was a critical feature of the conventional Heckscher–Ohlin model (Leamer et al. (1995)[34] & Xu [61]). Instead, researchers begun focusing their attention on data descriptions in studies on wage inequality in developed economies. Relaxing the Heckscher–Ohlin hypothesis of technological homogeneity allows capital deepening and skill-biased technological changes to be considered. This opens up new avenues to consider plausible countereffects in terms of the impacts of international trade on income distribution (Meschi and Vivarelli (2009)[43]). Calderòn and Chong (2001)[13] found that the long-run decline of income inequality is linked to increased trade volume.

Davis and Harrigan (2011)[20] combined the efficiency wage model of Shapiro and Stiglitz (1984)[55] with the trade model of Melitz (2003)[40] and demonstrated that, in the simplest model that transits autarky to trade liberalization, trade always destroys the best jobs, although liberalization in already partially open economies does not. However, the authors also showed that, if average wages increase, unemployment rates follow. In sum, inequality increases. Van Reenen (2011)[58] stated that since the early 1990s, labor markets have become more polarized, with jobs in the middle of the wage distribution becoming less common, while those in the bottom and top are increasing their relative shares. it is argued that trade may be the cause of this development. Artuç et al. (2010)[4] indicated that a worker's benefit from liberalization depended more strongly on their sector of employment than on their education.

Lim and McNelis (2016)[37] showed that increasing trade openness could lead to changes in income inequality, but its precise effect depends on the stage of development of the country. The authors used simulation with the dynamic stochastic general equilibrium model and calibration to demonstrate that the Gini coefficient of a country and trade openness could be negatively or positively correlated, depending on the capital intensity and the degree of openness. Overall, the results suggested that trade and financial openness could be effective policies for reducing inequality in low-income countries if these countries significantly increased the marginal productivity of labor through capital-intensive production methods. These findings are in line with the results of this study. Further, Lim and McNelis (2016)[37] suggested that trade and financial openness can be effective policies for reducing inequality in low-income countries, provided that they redistribute the capital gains. These conclusions were derived using empirical and simulation models.

Blanchard and Willmann (2016)[9] developed a model that revealed a number of related trends without using Gini index data. First, the authors observed that the past few decades have witnessed a sharp "hollowing out" of the middle class and medium-skilled employment in a broad set of industrialized countries. Second, trade liberalization and increased import competition were found to be at least partially responsible for some of the middle-class job losses and wage declines. Third, it was noted that, although some workers have responded to increased globalization by increasing their human capital investment, others have decreased their educational attainment.

The key finding of Lim and McNelis (2016)[37] was that increasing openness in both trade and finance was likely to have resulted in improvements in the Gini coefficient for economies that have reached sufficient capital-intensive production methods and income growth. The simulations suggested that increasing both trade and financial openness improves both income growth and equality, once an economy crosses a critical threshold in capital intensity and decreases the use of imported intermediate goods during the production process. This result indicates that policies to transform the capital intensity of non-traded production, especially in low-income countries, are likely to create an environment wherein further openness is beneficial for both income growth and equality. It is also worth noting that a higher degree of financial and trade liberalization may occur relatively efficiently because of the weaker political-economic pressures on protection when countries have already achieved a certain level of human capital accumulation and more equitable income distribution.

Menyah et al. (2014)[42] used a panel-causality approach and found that increases in trade openness and financial development do not support the hypotheses that finance- and trade-led economic growth occurred in African countries. These findings indicate that inter-country income inequality may have a negative relationship with trade liberalization, in addition to the potentially negative impact on intra-country income inequality, which is the focus of the present study.

Jauch and Watzka (2016)[30] showed that financial development primarily resulted in incremental changes in income inequality. This result was based on analysis using lagged values of the Gini coefficient, financial development, and GDP per capita as instruments in the generalized method of moments (GMM) Arellano–Bond estimator (Arellano and Bond[3]).

Using time-series analysis, Jalil (2012)[29] found a curvilinear relationship between openness and income inequality measures. Specifically, data from China for the period between 1952 and 2009 was analyzed using Gini coefficients and employing the framework of the Kuznets curve. By using individual time-series estimations, Daumal (2013)[19] explained the differences in the impact of trade openness on regional inequality in India and Brazil. India experienced more regional inequality with more trade openness. However, in Brazil, trade openness contributed to a decline in regional inequalities. Using Gini coefficients in both of these countries and per capita income data at the subnational level, Daumal (2013)[19] developed an indicator of regional inequality.

Considering relative income shares enables the whole income distribution of a country to be taken into account, whereas other inequality measures, such as the Gini coefficient, are less able to represent this information Dabla-Norris et al. (2015)[18]. Abdullah et al. (2015)[1] pointed out that 48% of the estimates of income inequality used the Gini coefficient and that relative income shares were a popular inequality measure. Thus, the income share of the top earners was considered particularly frequently. Because data on Gini coefficients are sparse, they are limited in their usefulness for analyzing the characteristics of inequality and macroeconomic variables (see Section 2.3 for linear panel regressions) and their yearly dynamics (see Section 2.3.3 for dynamic panel estimations using GMM). Longer periods than the one selected for the present analysis are required to use Gini coefficients as a measure of inequality.

Table 2.1: List of notations used in this paper

	Key notations used in this paper
$TOP1$	Top 1% income bracket
$TOP10$	Top 10% income bracket
$MIDDLE$	Income bracket between top 10% and 50%
$BOTTOM$	Bottom 50% income bracket
$SHARE$	Income Share
POP	Population
$GOVSPNED$	Share of government final expenditure in GDP (%)
$FINDEV$	Share of financial institution deposits in GDP and stock market capitalization (%)
$OPENNESS$	Share of the sum of imports and exports in GDP (%)
MFP	Multi-factor productivity (country specific and indexed at 100 in 2010)
$GDPpc$	GDP per capita (purchasing power parity based on 2011)
n	The number of individuals
T	The number of periods in the study
N	The number of observations

2.3 The Analysis of Panel Regressions

2.3.1 Variables and Their Data Sources

The period of time for which data are available for the top 1% income share is from 1966 to 2016; other data are available for shorter time periods. The countries that I analyze in this paper are Argentina, Australia, Bahrain, Brazil, Canada, Chile, China, Colombia, Cote d'Ivoire, Croatia, Czech Republic, Denmark, Egypt, Finland, France, Germany, Hungary, India, Indonesia, Iran, Iraq, Ireland, Italy, Japan, Jordan, South Korea, Kuwait, Lebanon, Malaysia, Mauritius, Netherlands, New Zealand, Norway, Oman, Portugal, Qatar, Russia, Saudi Arabia, Seychelles, Singapore, Slovenia, South Africa, Spain, Sweden, Switzerland, Turkey, the United States, the United Arab Emirates, the United Kingdom, and Uruguay.

$TOP1(n = 51)$, $TOP10(n = 47)$, $MIDDLE(n = 24)$, and $BOTTOM(n = 24)$ are available from the World Inequality Database (`https://wid.world`). POP, $GOVSPEND$, $FINDEV$, $OPENNESS$, and $GDPpc$ are sourced from World Bank Open Data (`https://data.worldbank.org/`). MFP is from OECD (2019). The definitions of these variables are provided in Table 2.1.

In this analysis, double-clustering standard deviations are used to estimate models, unless otherwise stated. Double-clustering standard deviations are robust in their cluster and with respect to serial correlation. The analyses were conducted using dynamic panel models with the GMM approach. Both the plain GMM dynamic panel model (Arellano and Bond (1991)[3]; Holtz-Eakin (1988)[27]) and a more elaborate version, the system GMM PVAR ([56]), were estimated. Time-effect dummies were excluded to avoid numerical calculation errors caused by multicollinearity, as I assumed that the impact of economic shocks on the relative income shares in a number of countries simultaneously (such as during the recession of 2007/08) is rare. Estimated standard errors are in parentheses; $. < 0.10$, $* < 0.05$, $** < 0.01$,

Table 2.2: Estimation Results of Equation (1)

	Type I ($n = 17$, $T = 16 - 31$, $N = 392$)	Type II ($n = 17$, $T = 17 - 31$, $N = 406$)	Type III ($n = 17$, $T = 16 - 31$, $N = 392$)
$\log(POP_{i,t})$	2.1067e-01 (1.3712e-01)	3.0125e-01 (1.5659e-01).	2.6907e-01 (1.4841e-01).
$GOVSPEND_{i,t}$	-2.4901e-01 (1.2315e-01)*	-2.4039e-01 (1.2951e-01).	-2.5050e-01 (1.3133e-01).
$FINDEV_{i,t}$	3.0124e-03 (6.2697e-04)***	1.3982e-03 (3.7709e-04)***	2.5421e-03 (6.6121e-04)***
$FINDEV_{i,t}^2$	-3.6540e-06 (1.1245e-06)**	NA	-2.9723e-06 (1.1039e-06)**
$OPENNESS_{i,t}$	1.2772e-03 (1.1938e-03)	5.9896e-03 (2.0704e-03)**	5.2620e-03 (2.0591e-03)*
$OPENNESS_{i,t}^2$	NA	-2.1482e-05 (6.2217e-06)***	-1.8316e-05 (6.1722e-06)**
$\log(MEP_{i,t})$	5.6971e-01 (2.5988e-01)*	6.1021e-01 (2.4361e-01)*	5.3762e-01 (2.5818e-01)*
R^2	0.64813	0.66612	0.65703

$. < 0.10 \quad * < 0.05 \quad ** < 0.01 \quad *** < 0.001$

Double clustered standard deviations are in parentheses.

and $*** < 0.001$ denote p-values; and R^2 is the adjusted R-squared.

2.3.2 Model for the Inverted U-shaped Relationship between Trade Openness and the Relative Share of the Top Income Bracket

In this subsection, the model estimation exemplifies the U-shaped relationship between financial development and the top income share bracket found in the literature (Jauch and Watzka (2016)[30]). A similar relationship between trade openness and the top income share bracket is also identified by testing the effects of the squared term of $FINDEV$ and $OPENNESS$. Because the population differs greatly in each country , and MFP is indexed at 100 in 2010 for OECD member countries, $\log(POP)$ and $\log(MFP)$ have been used instead of POP and MFP.

$$\begin{aligned}
&log(TOP1_{i,t}) \\
&= \beta_{POP} log(POP_{i,t}) + \beta_{GOV} GOVSPEND_{i,t} + \beta_{FIN} FINDEV_{i,t} + b_{FIN} FINDEV_{i,t}^2 \\
&+ \beta_{OPEN} OPENNESS_{i,t} + b_{OPEN} OPENNESS_{i,t}^2 + \beta_{MFP} log(MFP_{i,t}) \\
&+ \alpha_i + \varepsilon_{i,t}
\end{aligned} \tag{2.1}$$

These regression results indicate that the coefficient of $GOVSPEND$ is significant, while the coefficient of $OPENNESS$ is not. These estimation results are different from that of the baseline model, which is provided in Section 2.4.1. The estimation using the squared term of $GOVSPEND$ suggests that the model should not include this squared term and that the relationship between $\log(TOP1)$ and $GOVSPEND$ should be linear. These estimation results indicate the validity of the type-III estimations as follows.

From Equation (2.1) and Table 2.2, the growth rate of the income share of the top 1% income bracket relative to the economic variables considered can be derived. From the estimation results in Table 2.2, the relationship between $TOP1$ and $FINDEV$, which is obtained as follows, requires the consideration:

$$\frac{\frac{\partial TOP1}{\partial FINDEV}}{TOP1} = \beta_{FIN} + 2b_{FIN}FINDEV \tag{2.2}$$

Based on Equation (2.2) and Table 2.2, $FINDEV = 412.2058$ is the estimated value at which the growth rate of the top 1% income share ($TOP1$) regarding $FINDEV$ becomes negative. This estimation suggests that the growth in income inequality slows down when $FINDEV$ increases. It is noteworthy that, because the values of financial development of Switzerland, Singapore, and Malaysia is higher than 350, it is possible that these countries are able to achieve financial development and income equality simultaneously if this paper's estimation (2.1) is accurate. However, the estimation in this study does not include them because the OECD (2019) data do not cover them.

The growth rate of the top 1% income share and the relationship with other economic variables can be derived from Equation (2.2) and Table 2.2. For this estimation result, the key point of interest is the relationship between $TOP1$ and $OPENNESS$, which is obtained as follows:

$$\frac{\frac{\partial TOP1}{\partial OPENNESS}}{TOP1} = \beta_{OPEN} + 2b_{OPEN}OPENNESS \tag{2.3}$$

From Equation (2.3) and Table 2.2, $OPENNESS = 139.4097$ is the estimated value at which the growth rate of the top 1% income share ($TOP1$) turns negative with respect to $OPENNESS$. This estimation suggests that the growth rate of income inequality slows down when $OPENNESS$ increases. Singapore, Bahrain, Seychelles, Malaysia, Ireland, the United Arab Emirates, the Netherlands, and Iraq surpass this threshold, although Iraq has a value over this threshold only in 2003. However, this estimation (2.1) only includes Ireland and the Netherlands because OECD (2019) data are available for these countries.

From Equation (2.1) and Table 2.2, the critical values of $FINDEV$ and $OPENNESS$ at which the sign of the growth rate of the top 1% income share diverges are 424.6038 and 143.6449, respectively.

2.3.3 Dynamic Panel Models with Dynamic Effects

A dynamic panel model was estimated using the GMM (Arellano and Bond (1991)[3]; Holtz-Eakin et al. (1988)[27]) to consider the dynamic effects of the dependent and independent variables with several lags in the unbalanced panel data.

Considering the interactions between relative income shares and trade openness alone, the relationship appears to be very complicated when using three-term dynamic effects. Surprisingly, prior variations in trade openness when considered across two terms were found to have a more statistically significant impact on relative income shares. The signs of the

Table 2.3: Dynamic Panel Estimation; Dependent Variables: $\log(SHARE_{i,t})$

INCOME BRACKET	TOP1 (n=51, T=1-50, N=1392)	TOP10 (n=47, T=1-50, N=1258)	MIDDLE (n=24, T=1-50, N=525)	BOTTOM (n=24, T=1-50, N=525)
$\log(SHARE_{i,t-1})$	0.839689 (0.014919) ***	0.8354987 (0.0280070) ***	0.8739481 (0.0738306) ***	0.770587 (0.052387) ***
$\log(OPENNESS_{i,t})$	0.072197 (0.024795) **	0.0469283 (0.0210573) *	-0.0217855 (0.0106746) *	-0.046624 (0.019359) *
$\log(OPENNESS_{i,t-1})$	-0.045822 (0.029200)	-0.0360744 (0.0135933) **	0.0078729 (0.0111920)	0.025134 (0.018646)
$\log(OPENNESS_{i,t-2})$	0.054253 (0.019308) **	0.0364389 (0.0071799) ***	-0.0094648 (0.0090574)	-0.052790 (0.011759) ***

$. < 0.10 \quad * < 0.05 \quad ** < 0.01 \quad *** < 0.001$

Standard deviations are in parentheses (as for the dynamic panel models using GMM) and are also double-clustered, which means that the cluster and serial correlations are robust.

coefficients for the income bracket and trade openness were opposite in relation to $TOP1$ and $TOP10$ when compared to $MIDDLE$ and $BOTTOM$ income shares. This means that the estimation results show that the effects of trade openness are opposite between the richest and poorest sections of the income distribution.

Finally, the prevailing view that all independent variables have positive effects on the $TOP1$ income bracket variable, in line with $GDPpc$, is validated. However, this analysis suffers from multicollinearity because of the fixed-effects estimation of the linear panel models, as shown in the Section 2.4.1. The following dynamic panel GMM estimations can control for this endogeneity:

$OpennessI$ is a model without any lag, $OpennessII$ is a model with one lag, and $OpennessIII$ is a model with two lags.

By using the Openness I, Openness II, and Openness III models (the multi-term dynamic panel models), the dynamic effects of trade openness (denoted by $\log(OPENNESS_{i,t})$, $\log(OPENNESS_{i,t-1})$, and $\log(OPENNESS_{i,t-2})$) and GDP per capita have been captured. The interaction between GDP per capita and trade openness cannot be determined without multi-term dynamic effects.

These findings are based on an annually-calculated inequality index, which includes the top income share bracket, as well as the middle- and bottom-income share brackets). This is novel because, in the past, studies Calderón and Chong (2001)([13]) have relied on long-term inequality indexes, and in particular, Gini coefficients. Studies which are able to detect relatively short-term dynamic effects (e.g., lasting a few years) are not common.

Table 2.4: Dynamic Panel Estimation; Dependent Variables: $\log(GDPpc_{i,t})$

	Openness I ($n = 17$, $T = 19 - 26$, $N = 407$)	Openness II ($n = 17$, $T = 19 - 26$, $N = 407$)	Openness III ($n = 17$, $T = 19 - 26$, $N = 407$)
$\log(GDPpc_{i,t-1})$	0.633130 (0.059540)***	0.670119 (0.058101)***	0.6732592 (0.0700860)***
$\log(POP_{i,t})$	-0.090587 (0.134987)	-0.080464 (0.137665)	-0.0882119 (0.1334224)
$\log(GOVSPEND_{i,t})$	0.100207 (0.059826).	-0.108292 (0.050102)*	-0.1177217 (0.0439531)**
$\log(FINDEV_{i,t})$	0.037461 (0.010749)***	0.040493 (0.011471)***	0.0379190 (0.0130075)**
$\log(OPENNESS_{i,t})$	0.026232 (0.017321)	0.068489 (0.030534)*	0.0703429 (0.0338429)*
$\log(OPENNESS_{i,t-1})$	NA	-0.065967 (0.018477)***	-0.0910495 (0.0225627)***
$\log(OPENNESS_{i,t-2})$	NA	NA	0.0271000 (0.0087265)**
$\log(MFP_{i,t})$	0.688258 (0.096273)***	0.645119 (0.068665)***	0.6584342 (0.0692860)***

$. < 0.10 \quad * < 0.05 \quad ** < 0.01 \quad *** < 0.001$

Standard deviations are in parentheses (as in the dynamic panel models using GMM) and are also double clustered, which means that the cluster and serial correlations are robust.

Table 2.5: Estimation Results of Equations (2.4) and (2.5)

	$\log(TOP1)$	$\log(GDPpc)$	$\log(OPENNESS)$
$\log(TOP1_{i,t-1})$	0.2029 (0.0214)***	-0.0685 (0.0151)***	0.0264 (0.0329)
$\log(GDPpc_{i,t-1})$	-0.0593 (0.0018)***	0.2864 (0.0012)***	0.1076 (0.0028)***
$\log(OPENNESS_{i,t-1})$	0.0697 (0.0108)***	0.1291 (0.0094)***	0.0610 (0.0127)***
$\log(TOP1_{i,t-2})$	0.2333 (0.0258)***	-0.0831 (0.0156)***	0.0384 (0.0343)
$\log(GDPpc_{i,t-2})$	-0.0486 (0.0017)***	0.2706 (0.0016)***	0.1103 (0.0026)***
$\log(OPENNESS_{i,t-2})$	0.1003 (0.0141)***	0.1158 (0.0084)***	0.0845 (0.0148)***
$\log(TOP1_{i,t-3})$	0.2514 (0.0274)***	-0.0907 (0.0172)***	0.0595 (0.0394)
$\log(GDPpc_{i,t-3})$	-0.0499 (0.0015)***	0.2545 (0.0031)***	0.1224 (0.0021)***
$\log(OPENNESS_{i,t-3})$	0.0689 (0.0102)***	0.1035 (0.0056)***	0.1001 (0.0151)***
const	-0.0295 (0.0034)***	0.0398 (0.0019)***	0.0025 (0.0042)

$. < 0.10 \quad * < 0.05 \quad ** < 0.01 \quad *** < 0.001$

Double clustered standard deviations are in parentheses.

2.3.4 Panel Vector Autoregressions

The PVAR model estimation sheds light on the effect of government polic y on manipulating relative income shares in the context of trade openness. Section 2.3.2 indicates the importance of considering dynamic effects. For example, trade liberalization contributes to openness. Hence, a PVAR model which allows for p lags of m endogenous variables as follows should be considered:

$$\mathbf{y}_{i,t} = \mu_i + \sum_{l=1}^{p} \mathbf{A}_l \mathbf{y}_{i,t-l} + \varepsilon_{i,t} \tag{2.4}$$

Let $\mathbf{y}_{i,t} \in \mathbb{R}^m$ be an $m \times 1$ vector of endogenous variables for the ith cross-sectional unit at time t. Let $\mathbf{y}_{i,t-l} \in \mathbb{R}^m$ be an $m \times 1$ vector of lagged endogenous variables. Disturbances $\varepsilon_{i,t}$ are independently and identically distributed (i.i.d.) for all i and t with $\mathbb{E}[\varepsilon_{i,t}] = 0$ and $Var[\varepsilon_{i,t}] = \mathbf{\Sigma}_\varepsilon$. $\mathbf{\Sigma}_\varepsilon$ is a positive semi-definite matrix. Moreover, $\mathbf{y}_{i,t}$ has been specified as follows:

$$\mathbf{y}_{i,t} = (\log(SHARE_{i,t}), \log(GDPpc2011_{i,t}), \log(OPENNESS_{i,t}))^{\mathrm{T}} \tag{2.5}$$

The estimation method involves a first difference transformation method, a system GMM, and a two-step approach to the PVAR. The number of observations is 522, while the number of groups is 42 because data is sparse. Table 2.5 presents the estimation results.

Figure 2.1 shows that the model cannot predict any variable reliably. The confidence bands are too explosive to draw further inferences, and their forecast is meaningless because they decline into negative territories. However, the increase in the relative share of the top 1% income bracket exhibits a higher probability of an explosive growth rate for the same income share bracket five years later. "$\log(TOP1)$ on $\log(TOP1)$" indicates that the relative income share is expected to increase after a period of five years. If this forecasting is accurate, policies that increase the income share of the highest income earners (e.g., a policy of reducing capital gains tax) would have devastating results in terms of income inequality. However,

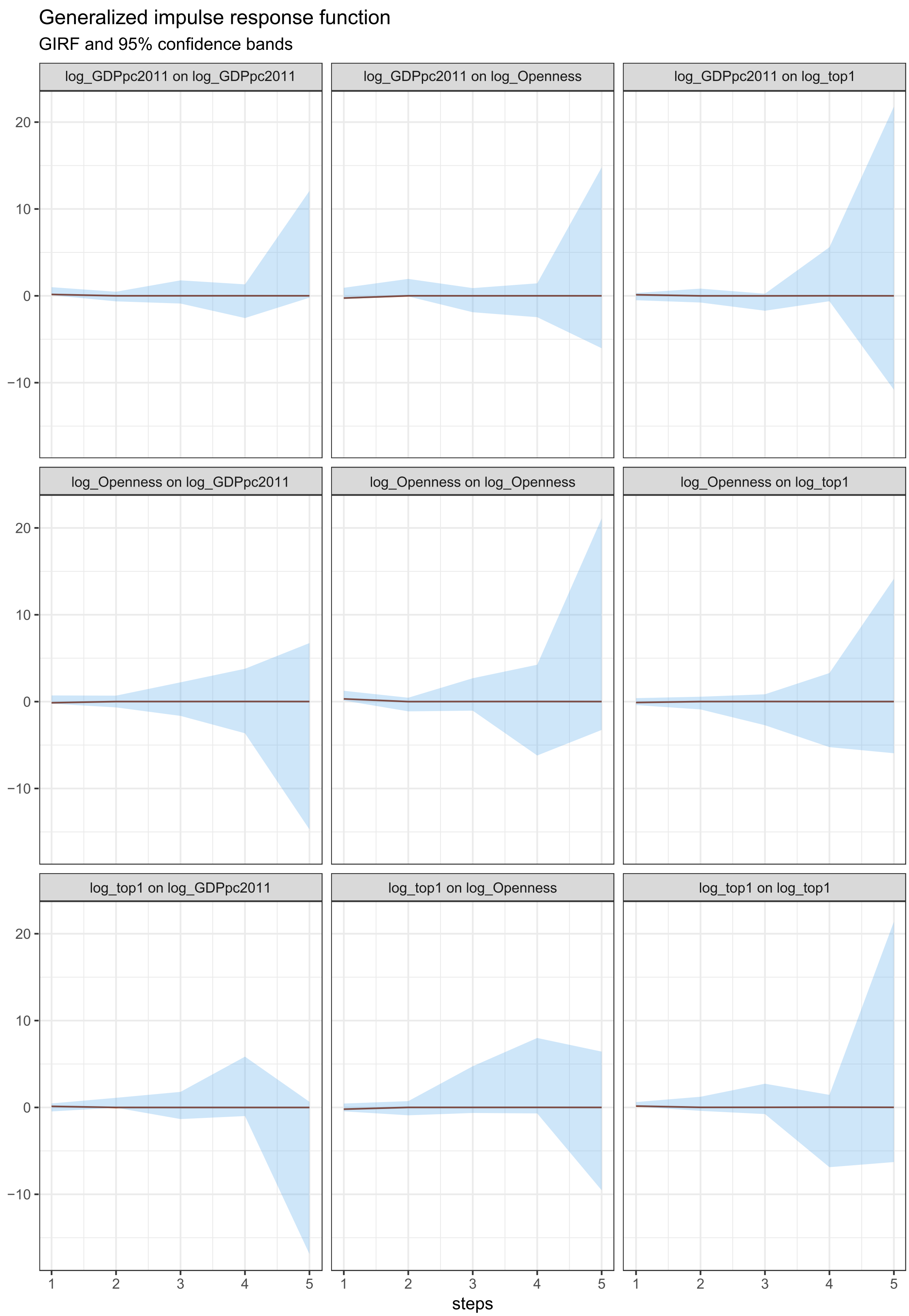

Figure 2.1: The Impulse Response Estimation of the PVAR Model

Table 2.6: Estimation Results of the Baseline Model

INCOME SHARE	TOP1 (n=17, T=17-31, N=406)	TOP10 (n=17, T=17-31, N=404)	MIDDLE (n=3, T=10-30, N=68)	BOTTOM (n=2, T=28-30, N=58)
$\log(POP_{i,t})$	0.294583 (0.152160) .	-0.019602 (0.109145)	-0.395456 (0.029557) **	-0.166825 (0.229457)
$\log(GOVSPEND_{i,t})$	-0.301150 (0.128322)	0.083007 (0.105043)	0.126159 (0.052178) ***	0.514811 (0.211923) *
$\log(FINDEV_{i,t})$	0.205238 (0.053598) ***	0.011995 (0.032041)	-0.032643 (0.015113)	0.319821 (0.048104) ***
$\log(OPENNESS_{i,t})$	0.171364 (0.078867) *	0.110258 (0.037009) **	-0.016561 (0.027823) **	-0.438979 (0.239345)
$\log(MFP_{i,t})$	0.505206 (0.240294) *	0.529706 (0.123948) ***	-0.054495 (0.010727)	-0.692802 (0.582688) .
R^2	0.66433	0.66584	0.82258	0.76039

$. < 0.10 \quad * < 0.05 \quad ** < 0.01 \quad *** < 0.001$

Double clustered standard deviations are in parentheses.

"$\log(GDPpc2011)$ on $\log(GDPpc2011)$" and "$\log(TOP1)$ on $\log(GDPpc2011)$" indicate that a growth policy enhances $GDPpc$ and lessens $top1$, respectively.

2.4 Non-dynamic Models

2.4.1 The Baseline Model

There are three advantages of the baseline model compared to the reference model, which is presented in the next section. First, the baseline model captures more economic variables that are statistically significant than the reference model. Second, MFP is a more concise variable than $GDPpc$ for explaining the cause of income inequality. Third, there are several studies on the interaction between income inequality and $GDPpc$, but only a few on the interaction between income inequality and MFP.

The estimations of $MIDDLE$ and $BOTTOM$ are based on panel estimations. The estimations suggest that these panel regressions do not circumvent the problem of spurious regression by eliminating the individual fixed effects.

Table 2.7: Estimation Results

	Within ($n = 18$, $T = 25 - 27$, $N = 476$)	Pooling ($n = 18$, $T = 25 - 27$, $N = 479$)
intercept	NA	3.2453059 (0.849124)***
$\log(POP_{i,t})$	0.908280 (0.208678)***	0.012190 (0.036928)
$\log(MFP_{i,t})$	1.247283 (0.093231)***	1.542255 (0.209980)***
R^2	0.91307	0.41455

. < 0.10 $\quad * < 0.05$ $\quad ** < 0.01$ $\quad *** < 0.001$

Double clustered standard deviations are in parentheses.

2.4.2 The Reference Model

The advantage of the reference model, compared to the baseline model, is that the degrees of freedom are larger because of the availability of dataset. However, the reference model has fewer statistically significant economic variables than the baseline model does. It is desirable that the reference model is not affected by the problem which a small number of the panel regressions on $MIDDLE$ and $BOTTOM$ in the baseline model framework have. The reference model employs $GDPpc$ as an explanatory variable instead of MFP and POP, as in the baseline model, to represent the macro-movement of economies.

In the reference model, the log-linearity of the estimation is used to validate the estimations, as well as to keep the consistency between the baseline model and the reference model, as shown in Table 2.8. Analysis of consistency is required for deducing the estimations of $MIDDLE$ and $BOTTOM$ in the panel regressions and ensuring that these are comparable with the time-series analyses that are inconsistent for the individual countries. Moreover, analysis of consistency between models in this paper's body and models in the Section 2.4 ensures that omitted variable bias is eliminated, based on the hypothesis that the baseline model is correct.

In the reference model, $GDPpc$ explains the dynamics of the relative share of the top income brackets, $TOP1$ and $TOP10$. However, little impact is observed in terms of the dynamics of the lower-income brackets, $MIDDLE$ and $BOTTOM$, in Reference Model II. This result indicates that the income share of 90% of the people in the economy may not be directly affected by GDP per capita growth. However, it should be noted that the results for $MIDDLE$ and $BOTTOM$ are more likely to be affected by measurement errors than the results for $TOP1$ and $TOP10$. The method of the estimation on income shares ($TOP1$, $TOP10$, $MIDDLE$ and $BOTTOM$) is based on the tax revenue from individuals in the past. $TOP1$ and $TOP10$ are accurate because top income earners are captured better than middle or bottom income earners.

2.5 The Dynamic Panel Models Without the Multi-Term Structure

These regressions indicate that the impact of the change of trade openness is different among different income brackets because the signs of the $OPENNESS$ coefficient differ when $TOP1$

Table 2.8: Estimation Results of the Reference Model

INCOME SHARE	TOP1 ($n = 42$, $T = 1 - 26$, $N = 737$)	TOP10 ($n = 29$, $T = 1 - 26$, $N = 688$)	MIDDLE ($n = 19$, $T = 1 - 26$, $N = 309$)	BOTTOM ($n = 19$, $T = 1 - 26$, $N = 309$)
$\log(GOVSPEND_{i,t})$	-0.029387 (0.070275)	0.079731 (0.060270)	0.025905 (0.037415)	0.057014 (0.085214)
$\log(FINDEV_{i,t})$	0.156342 (0.045755) ***	0.035574 (0.025112) **	-0.026816 (0.030446)	0.014909 (0.034338)
$\log(OPENNESS_{i,t})$	0.285879 (0.040129) ***	0.285879 (0.040129) ***	-0.099782 (0.051581) .	-0.22160 (0.044102) ***
$\log(GDPpc_{i,t})$	0.144746 (0.046977) **	0.108122 (0.037693) **	-0.064308 (0.042890)	-0.065315 (0.074070)
R^2	0.50315	0.47739	0.33012	0.16692

$. < 0.10 \quad * < 0.05 \quad ** < 0.01 \quad *** < 0.001$

Double clustered standard deviations are in parentheses.

and $BOTTOM$ are compared. These models are consistent with the non-dynamic panel regressions in Section 2.4. This estimation and the dynamic panel estimations examined have, at the least, strongly significant first-order serial correlations. Therefore, the lag of dependent variables in the dynamic panel models must be taken, as previously described.

2.6 Conclusion

The results of the dynamic panel data regressions (and the non-dynamic models in Section 2.4) are consistent with the argument by Piketty (2015)[50] that the globalization's move in favor of the wealthiest 1%. Using a relatively short time-series analysis, it is not possible to effectively estimate the interaction between relative income shares and key economic variables. However, this study identified a few variables that have affected the income distribution in individual countries. The analysis revealed that the dynamic interaction between trade openness and relative income shares or GDP per capita was more complicated in terms of dynamic effects than what other models have been able to identify (Table 2.3). Specifically, trade openness has opposite effects on different income shares such as $TOP1$, $TOP10$, $MIDDLE$ and $BOTTOM$.

Furthermore, dynamic panel estimation using GMM shows that trade openness has multi-term dynamic effects on income inequality, which is also a new finding in the literature on income distribution. At the same time, estimation using PVAR shows that trade openness has dynamic effects. Specifically, an adverse effect on income inequality is found, and evidence suggests that GDP per capita decreases. Another possible implication of the study's findings concern policy effects on income inequality in the context of trade openness.

Table 2.9: Estimation Results of Appendix B

INCCME SHARE	TOP1 (n=42, T=1-26, N=737)	TOP10 (n=39, T=1-26, N=688)	MIDDLE (n=19, T=1-26, N=309)	BOTTOM (n=19, T=1-26, N=309)
$\log(SHARE_{i,t-1})$	0.628041 (0.053374) ***	0.7533374 (0.0335800) ***	0.7392217 (0.1061680) ***	0.7382833 (0.0591555) ***
$\log(GOVSPEND_{i,t})$	-0.039271 (0.045243)	0.0227806 (0.0209096)	0.0274336 (0.0279505)	-0.0089059 (0.0453593)
$\log(FINDEV_{i,t})$	0.055756 (0.018455) **	-0.0024736 (0.0083332)	-0.0015282 (0.0086114)	0.0404984 (0.0196088) *
$\log(OPENNESS_{i,t})$	0.119493 (0.024195) ***	0.0544383 (0.0138321) ***	-0.0378160 (0.015482)	-0.0781836 (0.0191202) ***
$\log(GDPpc_{i,t})$	0.018796 (0.023923)	0.0254599 (0.0114350) *	-0.0187484 (0.0182694)	-0.0439626 (0.0197014) *

. < 0.10 $\quad * < 0.05$ $\quad ** < 0.01$ $\quad *** < 0.001$

Double clustered standard deviations are in parentheses.

In short, the dynamic effects identified using the models in this study confirm that multi-term analyses are required to explain the interaction between income inequality and other economic variables. This finding requires further research, for instance, to consider the compositions of consumption.

Chapter 3

Total Fertility Rates in Japan and Other Variables

3.1 Introduction

In 2019, only 864 thousand babies were born in Japan, with 126 million population, the number is the lowest in the statistics, and the percentage is only 0.69%. Several academics and journalists cite the chronically low birth rates as one of Japan's crucial challenges. Because East Asian countries have similar problems, and even the United States now records the lowest birth rates in its history, the mechanism between the total fertility rates (TFRs) and other socio-economic variables are supposed to be vital to find the solution and evaluate the policy on low total fertility rates.

Numerous people suggest that income inequality and educational costs have adverse effects on TFRs. One may question if TFRs relate to the Gini index and the admission rates to colleges and the age cohort, and one may also be interested in the time series structure of TFRs.

Several papers suggest that the factors affect TFRs, such as female employment, male and female wage, wealth transfer between the generations, parental care costs, the number of children in one household. Moreover, in Japan, the policies to promote parental care should be evaluated as well. However, researchers have not estimated the relationship between the fertility rates, the Gini index, and the admission rates after high schools.

The spatial panel data analyses show that the increase of the Gini index has adverse effects on TFRs. Also, the relationship between the population density and TFRs is the inverted U-shape. Furthermore, real expenditure and TFRs have an inverted J-shape relationship. Then, the impulse response of the panel vector autoregression (Sigmund & Ferstl 2019[56]) indicates that even a one-shot policy on TFRs has favorable effects for about 20 years and adverse economic shocks have opposite effects. This paper's methods also validate the Easterlin hypothesis on fertility (Macunovich & Easterlin 2018[39]). This paper shows that the negative relationship between TFRs and the population density is inverted-U-shaped, using the simple unbalanced panel data with large cross-sectional dimensions and the balanced panel data with smaller cross-sectional dimensions and denser time-series ones. The bivariate nonparametric regression and time series of Moran I and Theil indices indicate the negative relationship between TFRs and colleges' admission rates. However, the panel non-Granger causality test and the spatial panel regression do not show a clear relationship between TFRs and the admission rates.

3.2 The Literature and Data Characteristics

3.2.1 The Literature

Economic and Analytical Studies on Total Fertility Rates

Several social scientists work on human fertility. However, here we focus on socio-economic approaches.

Becker (2009)[7] considers the interaction between the quantity and quality of children to explain why education per child tends to be lower in families having more children.

Willis (1973)[60] points out that the interaction model captures an essential empirical regularity in the cross-section relationship between fertility and measures of husband's income and wife's education that has become apparent in the emergence of a U-shaped relationship between fertility and income. The predictions of the theoretical model of fertility demand developed in his paper fit well with this paper's estimation result.

Prettner et al. (2013)[51] theoretically and empirically show that if individuals put more weight on education, they reduce fertility, increase educational investments, and hold consumption, savings, and health investments constant.

Lutz et al. (2006)[38] empirically find a consistent and significant negative relationship between human fertility and population density, using fixed-effects models on the time series of 145 countries and controlling for critical social and economic variables such as GDP per capita, infant mortality, female labor force participation, and female literacy. In the empirical study, Kulu (2013)[33] shows that the desired family size in small towns and rural areas is larger than that in urban areas.

Myrskylä et al. (2009)[46] find that TFRs in highly developed countries have inverted J-shape curves over the Human Development Index (HDI) except Japan, Canada, and South Korea. The HDI is a summary measure of average achievement in key dimensions of human development: a long and healthy life, being knowledgeable and having a decent living(United Nations Development Programme's Human Development Report[52]). However, their finding is not robust to the redefined HDP or the decomposition of the HDI into its subindices of education, the standard of living, and health (Harttgen & Vollmer 2014[26]).

Aldieri & Vinci (2012)[2] estimate the correlation between the female's education and her number of children in Italy, and use the partner's education to take into account the family dimension. They use a zero-inflated Poisson regression and observe a negative correlation between the number of children born and the educational level.

Sociological and Demographic Studies on Total Fertility Rates

As Pampel & Peters (1995)[47] review the Easterlin hypothesis, Easterlin presented his basic argument that swings in relative cohort size and resulting levels of relative income among cohorts of child-bearing age produced the baby boom and then the baby bust. Initially, his discussion is concerned with describing demographic cycles (Easterlin 1968[22]). Moreover, the linkage between higher birth rates and adverse social-economic effects arises because large cohorts face crowding problems in three major social institutions, such as the family, education, and labor markets (Macunovich & Easterlin 2018[39]).

The second demographic transition (SDT) explains the inverted J-shape curve in sociology and demography as before. Zaidi & Morgan (2017)[62] summarize the SDT has three arguments: the shift from king-child to king-couple, the Maslowian drift, and the rise of individualism, and pushback against economic explanations.

Studies on Total Fertility Rates in Japan

Gini Index

Few researchers have the Gini index as the explanatory variable to total fertility rates. The panel data in this study (Kamihigashi & Sasaki, 2020) shed light on the Gini index's effects on TFRs.

Educational level

Some papers regress the female educational levels to TFRs.

3.2.2 Data

Total Fertility Rates (TFR) and the population of each cohort of every prefecture ($p0to4$, $p5to9$, $p10to14$, $p15to19$, $p20to24$, $p25to29$, $p30to34$, $p35to39$, $p40to44$, $p45to49$, $p50to54$, $p55to59$, $p60to64$, $p65to69$, $p70to74$, $p75to79$ and $pover80$) are from the National Institute of Population and Social Security Research (Japan) and its former organization. Municipal data on TFR is available online from the Statistical Bureau of Japan.

Figure. 3.1 depicts the movements of total fertility rates of each prefecture in Japan.

3.3 Results of the Econometric Approaches

3.3.1 Nonparametric Analysis and the Panel Non-Granger Causality

At first, one can nonparaemtrically regress the bivariate relationship between the total fertility rates (TFRs) and other socio-economic variables. Figure 3.2 shows the relationship between TFR and *pop_density* and one between TFR and *ad_rate* appear inverse corrletions.

The relationship between TFR and *pop_density* and one between TFR and *real_exp_mean_*100 have the panel Granger causality in both directions. These tests are based on Dumitrescu & Hurlin (2012)[21]. They note that the null of Homogeneous Non-Causality does not provide any guidance concerning the number or the identity of the particular panel units for which the null of non-causality is rejected. In other words, only non-Granger causality is meaningful. However, *gini* and *ad_rate* have the panel Granger causality from TFR, and TFR has the panel non-Granger causality from *gini* and *ad_rate*. This *gini* and *ad_rate* do not determine TFR in the non-Granger causality standpoint. Then, the panel non-Granger Causality test assumes that the individuals of the panel have no cross-sectional dependence.

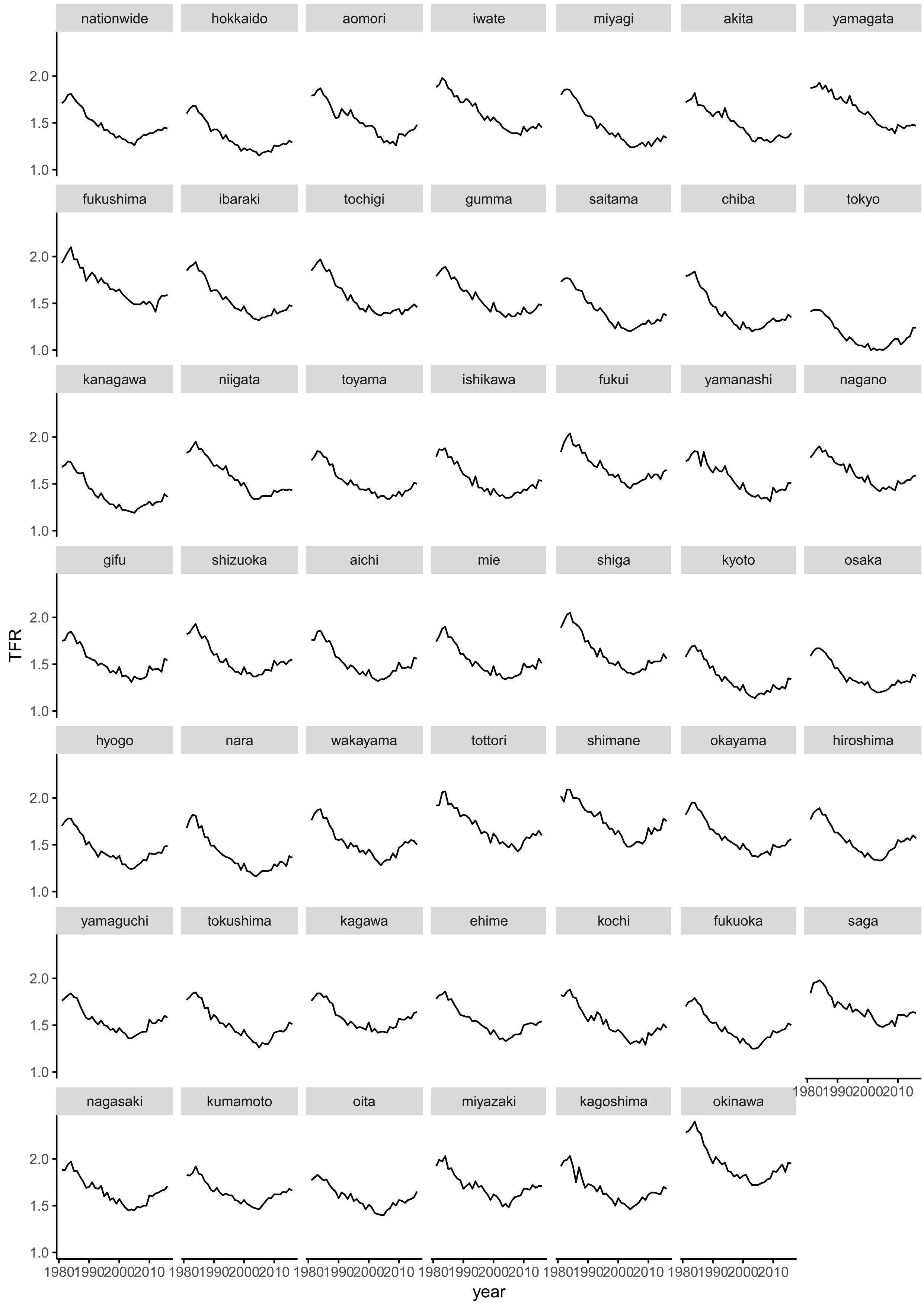

Figure 3.1: Total Fertility Rates in Prefectures

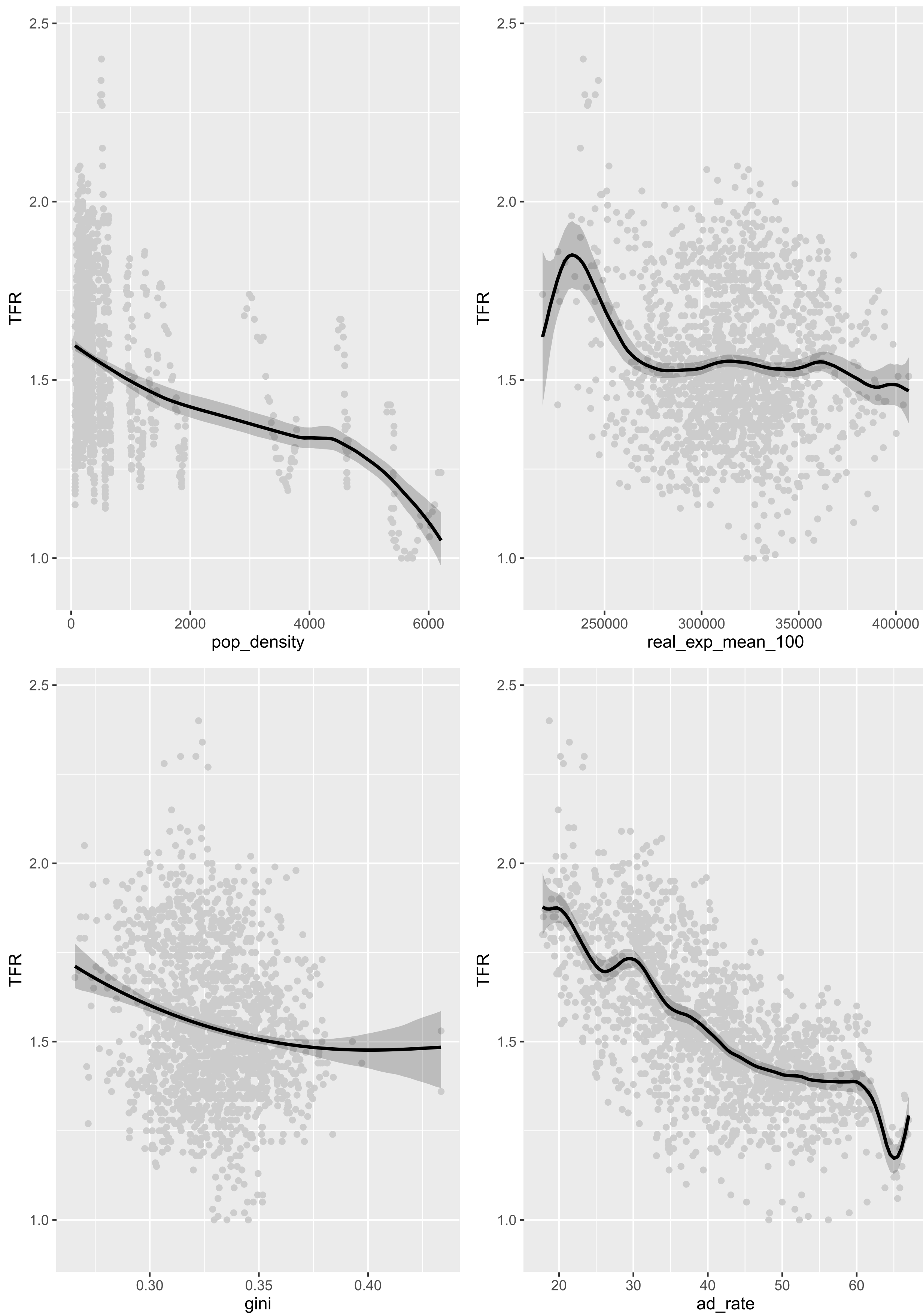

Figure 3.2: Nonparametric Regression Results

Table 3.1: Estimation Results: The Large Cross-Sectional Panel ($n = 3755$, $T = 1 - 7$, and $N = 19235$)

$\log(TFR)$	Fixed Effects	Random Effects	Pooling
Intercept		0.2332224 (0.0154558) ***	0.36260635 (0.01481855) ***
$\log(pop\_density)$	0.6627606 (0.0654288) ***	0.1294545 (0.0057179) ***	0.08314563 (0.00562807) ***
$(\log(pop\_density))^2$	-0.0504881 (0.0056033) ***	-0.0140688 (0.0005074) ***	-0.01043975 (0.00051242) ***
$Adj.R^2$	-0.11254	0.16	0.19968

$. < 0.10 \quad * < 0.05 \quad ** < 0.01 \quad *** < 0.001$

Double clustered standard deviations are in parentheses.

3.3.2 The Relationship Between the Total Fertility Rates in the Municipal Level and the Population Density

Because municipal data on TFR have relatively large cross-sections (at least a few thousand) and seven terms, panel data analysis is available. The estimation is based on the fixed-effects model, and the Least Square Dummy Variable as explanatory variables are few, and the omitted variables bias is severe. The Hausman test between the fixed effects and the random effects supports this reasoning.

$$exp(0.6627606/2(0.0504881)) = 708.7712 \tag{3.1}$$

This subsection's relationship between the TFR and $pop\_density$ (Table 3.1) is similar to that of the spatial panel data analysis (Table. 3.2) in this paper because the relationship is the inverted-U shape, and the local maximum (708.7712 persons per km^2) of the inverted-U form has the value similar to the spatial panel data analysis (797.171 persons per km^2) (Equations (3.1) and (3.8), respectively). Next, we focus on spatial autocorrelation as the cross-sectional dependence.

3.3.3 The Spatial Autocorrelation and the Inequlity Index

Moran's I in the spatial autocorrelation of cross-sectional spatial data has an analogy to Durbin-Watson in the serial autocorrelation of time-series data (Li et al., 2007[36]). Then, the higher Moran's I is, the higher the degree of spatial autocorrelation is. The spatial dependence (global spatial autocorrelation) measure of Moran's I is represented by equation 3.2 (the formulation follows Rey 2004[54]):

$$Moran\_I_t = \frac{n}{s}\frac{\sum_i \sum_j w_{ij} z_{it} z_{jt}}{\sum z_{it}^2} \tag{3.2}$$

$$\tag{3.3}$$

where n is the number of prefectures (i.e.$n = 47$), z_{it} and z_{jt} are the deviation of each variable from the mean of each prefecture in each year (the prefecture i, j and the year t), w_{ij} are the elements of weight matrix W $(n \times n)$ and it is equal to 1 if i and j are neighbors and 0 if they are not; s is the sum of all elements of W (spatial weights). One note that n, s and w_{ij} are invariant over time.

Figure 3.3 plots Moran's I of each variable. The critical value which rejects at the significant level 0.05 null hypothesis that there is no spatial correlation is about 0.14 in the case of this dataset and is added as *The Critical Value*(horizontal lines) in line plots of Figure 3.3.

According Rey (2004)[54], Figure 3.4 plots Moran's I and Theil index of each variable. The Theil index of inter-prefecutral inequalities is presented as follows(the formulation follows Cowell 2011[17]):

$$Theil_t = \frac{1}{n} \sum_{i=1}^{n} \frac{y_{it}}{\mu_t} \log(\frac{y_{it}}{\mu_t}) \tag{3.4}$$

where y_{it} is the value of each variable in each prefecuture and each year, μ_t is the mean over Japan in each year and n is the number of prefectures(i.e.$n = 47$). Rey (2004)[54] empirically shows higher Moran's Is tend to be higher Theil indices. Theil indices have the drawback that they are affected by the sample size. With higher inequality of TFR, ad_rate has lower inequality over 36 years in this paper's dataset. Figure 3.4 indicates that inequality of TFR and that of ad_rate have a negative relationship, and one must consider geographical inequality to analyze the relationship of both. Next, we focus on spatial panel regression as the model of spatial autocorrelation.

3.3.4 The Spatial Panel Data Analysis

Hsiao (2014)[28] suggests that panel data analysis could control the impact of omitted variables (or individual or time heterogeneity) and generate more accurate predictions for individual outcomes than the cross-sectional analysis and time-series analysis.

One can apply the spatial panel data analysis to the analysis of Total Fertility Rates (TFRs) to gain more efficiency than the static panel analysis such as the Least Squares Dummy Variable (LSDV) or the dynamic panel analysis such as the dynamic panel Generalized Method of Moments (GMM) (Arellano & Bond, 1991[3]).

One can conduct the Maximum Likelihood (ML) (Baltagi et al. 2007[6]) and the Generalized Moments (GM) estimation (Kapoor et al. 2007[32]) to estimate the spatial panel. In this paper, the fixed effects spatial error model is estimated because the fixed effects model is generally more appropriate than the random effects model since adjacent spatial units' space-time data are located in unbroken study areas (Elhorst 2014[23]). Furthermore, as the spatial error model's parameters are considered marginal effects themselves (Elhorst 2014[23]), these parameters are easily interpretable. Then, other models using the spatial weight matrix are similar to the spatial error model as follows. This paper's notations are based on Millo and Piras (2012)[45], and we use their package. This paper utilizes three models to control spatial autocorrelation. The first one takes the spatial error terms into the error terms. Second, the spatial lag terms are taken into the estimation equation. In the third model, both spatial terms are considered.

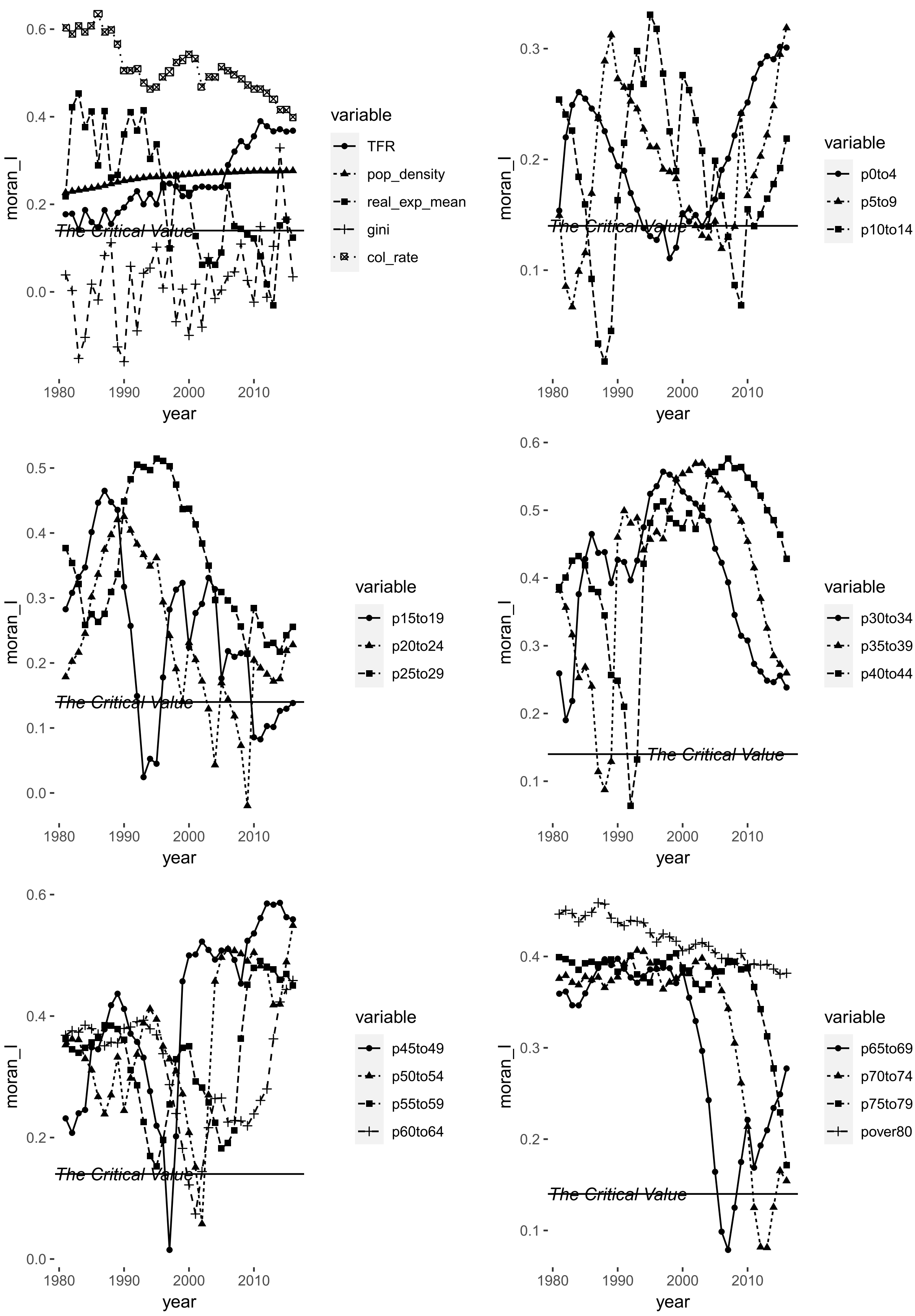

Figure 3.3: Moran's I of Each Variable in This Study

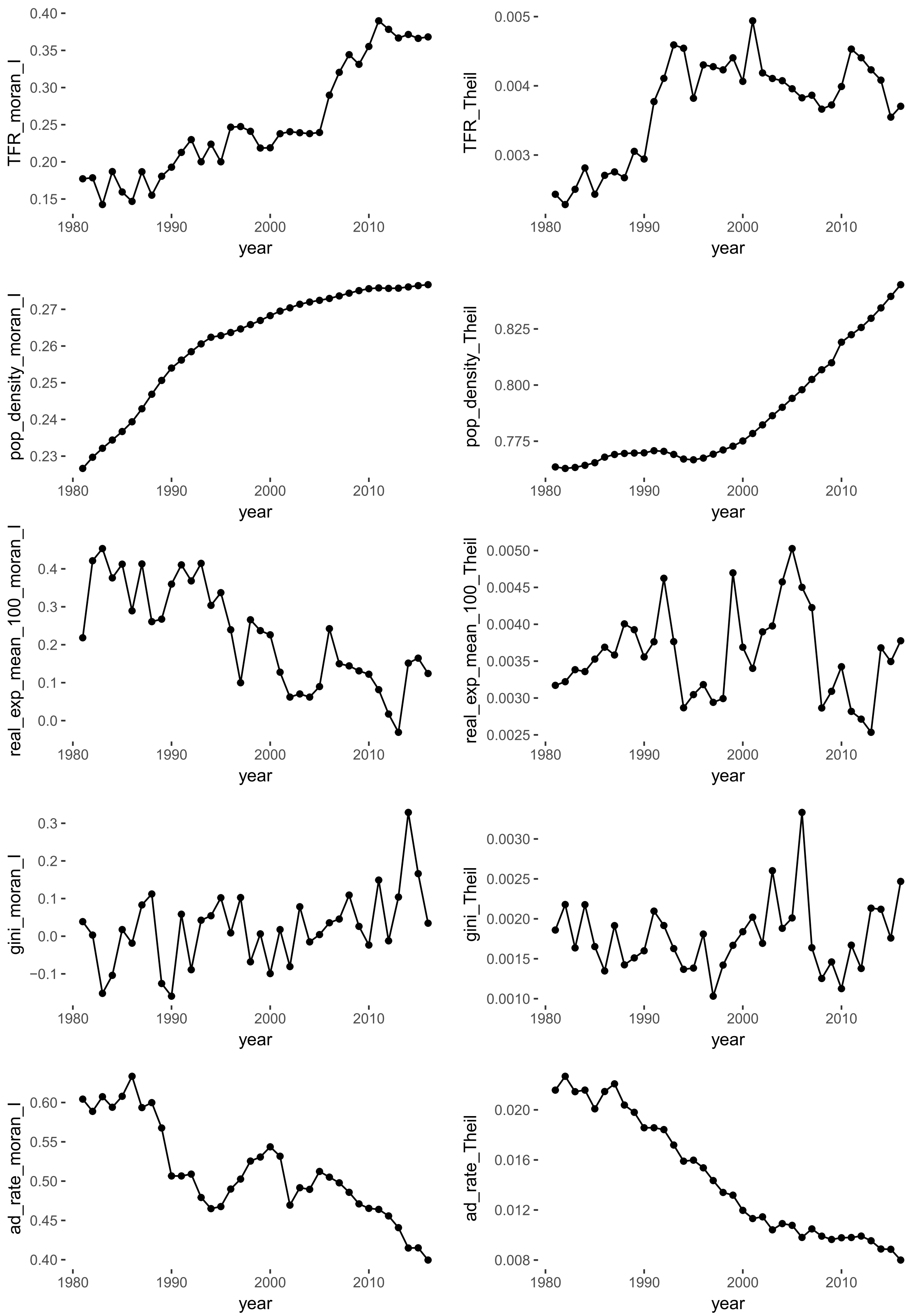

Figure 3.4: Moran's I and Theil Index of Each Variable in This Study

The fixed effects spatial error panel data model estimated by the ML and the GM in this paper is as follows:

$$y = (\iota_T \otimes I_N)\,\mu + X\beta + \varepsilon \tag{3.5}$$

$$\varepsilon = \rho\,(I_T \otimes W_N)\,\varepsilon + \nu \tag{3.6}$$

$$\tag{3.7}$$

y is the $NT \times 1$ vector of the dependent variable (here $\log(TFR)$), μ the vector of the time-invariant fixed effect (not spatially autocorrelated), and X the $NT \times k$ of independent variables. Also, ι_T is the vector of $T \times 1$ ones, I_N the identity matrix with $N \times N$ dimensions, I_T the identity matrix with T dimensions, and W_N the spatial weight matrix. ε is $\varepsilon_{it} \sim IID(0, \sigma_\varepsilon^2)$ error terms, and ν is $\nu_{it} \sim IID(0, \sigma_\nu^2)$. Moreover, β is the parameter vector, and ρ ($|\rho| < 1$) is the spatial autocorrelation coefficient. $\otimes$ represents the Kronecker product.

Table 3.2: Spatial Error Model Estimation Results: Spatial Panel Maximum Likelihood (SPML), Spatial Panel Generalized Moments (SPGM), Least Squares Dummy Variable (LSDV) and Dynamic Panel Generalized Methods of Moments (Arellano & Bond 1991[3])(DPGMM(AB)) ($n = 47$, $T = 36$, and $N = 1692$)

$\log(TFR)$	SPML	SPGM	LSDV	DPGMM(AB)
ρ	0.719627 (0.019831) ***	0.48523842		
σ_ν^2		0.00048547		
lag				0.2899992 (0.0339438) ***
log(*pop_density*)	0.32304894 (0.08311636) ***	0.2901936 (0.0896074) **	0.2058188 (0.2080846)	0.2873582 (0.3298953)
$(\log(pop\_density))^2$	-0.02417644 (0.00662936) ***	-0.0165459 (0.0071636) *	-0.0055649 (0.0159123)	-0.0121894 (0.0255364)
log(*real_exp_mean*)	-6.91076549 (1.10683036) ***	-6.9440267 (1.2098719) ***	-6.6905334 (1.9759554) ***	-3.8347270 (2.2872339) .
$(\log(real\_exp\_mean))^2$	0.27298465 (0.04375230) ***	0.2742781 (0.0478285) ***	0.2648269 (0.0781029) ***	0.1533209 (0.0904619) .
log(*gini*)	-0.02910955 (0.00939272) **	-0.0322535 (0.0103164) **	-0.0416469 (0.0129451) **	-0.0471380 (0.0156444) **

$\log(ad\_rate)$	-0.04643822 (0.00676260) ***	-0.0462737 (0.0073256) ***	-0.0438069 (0.0151636) **	0.0155533 (0.0229694)
$\log(p0to4)$	0.89394662 (0.02606008) ***	0.8703380 (0.0271727) ***	0.7081305 (0.0550405) ***	0.2848333 (0.0511087) ***
$\log(p5to9)$	-0.21758129 (0.02996316) ***	-0.1699873 (0.0316602) ***	-0.0051924 (0.0596648)	0.1764584 (0.0504613) ***
$\log(p10to14)$	0.05587594 (0.02365141) *	0.0650945 (0.0251235) **	0.0942250 (0.0369565) *	-0.0416069 (0.0376131)
$\log(p15to19)$	-0.02876705 (0.01680870) .	-0.0931509 (0.0171463) ***	-0.1860473 (0.0298778) ***	-0.2156280 (0.0325960) ***
$\log(p20to24)$	-0.09850934 (0.01339883) ***	-0.1191109 (0.0134301) ***	-0.1283993 (0.0229226) ***	-0.1715923 (0.0198345) ***
$\log(p25to29)$	-0.30391512 (0.01841837) ***	-0.3529571 (0.0179476) ***	-0.3498440 (0.0327864) ***	-0.2333846 (0.0396871) ***
$\log(p30to34)$	-0.27015279 (0.02290737) ***	-0.2967724 (0.0222323) ***	-0.3533845 (0.0422245) ***	-0.3463369 (0.0422883) ***
$\log(p35to39)$	-0.06360327 (0.01634914) ***	-0.1092323 (0.0150501) ***	-0.1149847 (0.0291976) ***	-0.1088752 (0.0452221) *
$\log(p40to44)$	-0.07534125 (0.01557907) ***	-0.0878620 (0.0144506) ***	-0.0982335 (0.0290015) ***	-0.0884292 (0.0360836) *
$\log(p45to49)$	0.00189920 (0.01524041)	0.0006549 (0.0139415)	-0.0136575 (0.0223707)	-0.0393289 (0.0384459)
$\log(p50to54)$	-0.01259816 (0.01495971)	-0.0085050 (0.0131295)	0.0289926 (0.0202256)	0.0044685 (0.0327516)
$\log(p55to59)$	-0.00069374 (0.01409659)	-0.0077085 (0.0116932)	-0.0150254 (0.0107741)	-0.0203795 (0.0214776)
$\log(p60to64)$	-0.05508316 (0.01414426) ***	-0.0637093 (0.0118807) ***	-0.0591934 (0.0120286) ***	-0.0502398 (0.0166956) **
$\log(p65to69)$	-0.00841575 (0.01566630)	-0.0113852 (0.0138455)	-0.0167431 (0.0175845)	-0.0427284 (0.0204149) *
$\log(p70to74)$	-0.01388993 (0.01743796)	-0.0155459 (0.0164233)	-0.0015067 (0.0183789)	0.0167357 (0.0173135)

$\log(p75to79)$	-0.00521812 (0.01723673)	-0.0516927 (0.0168845) **	-0.1224916 (0.0266901) ***	-0.1479913 (0.0290800) ***
$\log(pover80)$	-0.01307586 (0.01487232)	-0.0067358 (0.0158047)	0.0137243 (0.0335773)	-0.0656447 (0.0450718)
$adj.R^2$			0.94194	

$. < 0.10 \quad * < 0.05 \quad ** < 0.01 \quad *** < 0.001$ Standard deviations are in parentheses.

$$exp(0.32304894/2(0.02417644)) = 797.171 \tag{3.8}$$

$$exp(6.91076549/2(0.27298465)) = 314,202 \tag{3.9}$$

pop_density has the local maximum at 797.171 persons per km^2(Equation(3.8)). Tokyo, Osaka, Kanagawa, Saitama, Aichi, Chiba and Fukuoka surpass this threshold. And, the median and the mean of *pop_density* are 272.0492 and 632.1765 respectively. *real_exp_mean* has the local minimum at $314,202$ yen(Equation(3.9)). Because median and the mean of *real_exp_mean* are $316,166.2$ and $351,621.2$ respectively, this threshold is approximate to the median and the mean.

To control age-structure, variables such as age-specific proportions (from $p0to4$ to $pover80$) imply young population proportions have negative impacts on the TFR, and this estimation results fit well the Easterlin hypothesis that young cohort sizes have adverse effects on their fertility (Easterlin 1968[22]).

$$y = (\iota_T \otimes I_N)\,\mu + \delta\,(I_T \otimes W_N)\,y + X\beta + \nu \tag{3.10}$$

Table 3.3: Estimation Results: The Dependent Variable Spatial Lag ($n = 47$, $T = 36$, and $N = 1692$)

$\log(TFR)$	2.5%	25%	50%	75%	97.5%
$\log(pop\_density)$	0.343655	0.541186	0.643823	0.744623	0.943435
$(\log(pop\_density))^2$	-0.078106	-0.062817	-0.054478	-0.046241	-0.030031
$\log(real\_exp\_mean)$	-14.735792	-12.054653	-10.613576	-9.194733	-6.490601
$(\log(real\_exp\_mean))^2$	0.257927	0.365099	0.421303	0.478313	0.584089
$\log(gini)$	-0.094378	-0.070903	-0.059344	-0.047504	-0.024879
$\log(ad\_rate)$	-0.090159	-0.074035	-0.065625	-0.057237	-0.041244
$\log(p0to4)$	0.869426	0.940574	0.977578	1.016849	1.094348
$\log(p5to9)$	-0.192202	-0.127373	-0.092455	-0.058033	0.005846
$\log(p10to14)$	-0.028012	0.022684	0.050234	0.077329	0.129743
$\log(p15to19)$	-0.173121	-0.137583	-0.118777	-0.100735	-0.065152
$\log(p20to24)$	-0.135510	-0.109293	-0.095367	-0.081996	-0.055562
$\log(p25to29)$	-0.439003	-0.396242	-0.374266	-0.352953	-0.312827
$\log(p30to34)$	-0.405093	-0.358098	-0.333778	-0.309284	-0.265107

$\log(p35to39)$	-0.136863	-0.106776	-0.091001	-0.074961	-0.044733
$\log(p40to44)$	-0.112777	-0.083861	-0.068743	-0.053439	-0.025284
$\log(p45to49)$	-0.033058	-0.007024	0.006675	0.020409	0.045720
$\log(p50to54)$	-0.031933	-0.008688	0.003372	0.015195	0.038383
$\log(p55to59)$	-0.045165	-0.025969	-0.015886	-0.006148	0.013126
$\log(p60to64)$	-0.105679	-0.086489	-0.076923	-0.067350	-0.048520
$\log(p65to69)$	-0.040240	-0.017628	-0.005402	0.006386	0.029322
$\log(p70to74)$	0.019658	0.048639	0.063993	0.079058	0.107305
$\log(p75to79)$	-0.131970	-0.100150	-0.083137	-0.066609	-0.036062
$\log(pover80)$	-0.006881	0.026490	0.043951	0.061570	0.093625

$$y = (\iota_T \otimes I_N)\,\mu + \delta\,(I_T \otimes W_N)\,y + X_t\beta + \varepsilon \tag{3.11}$$

$$\varepsilon = \rho\,(I_T \otimes W_N)\,\varepsilon + \nu \tag{3.12}$$

Table 3.4: Estimation Results: The Dependent Variable and Error Spatial Lag ($n = 47$, $T = 36$, and $N = 1692$)

$\log(TFR)$	2.5%	25%	50%	75%	97.5%
$\log(pop\_density)$	-0.037670	0.0273568	0.060570	0.093789	0.157603
$(\log(pop\_density))^2$	-0.016809	-0.0119725	-0.009378	-0.006858	-0.001985
$\log(real\_exp\_mean)$	-4.763105	-4.0040306	-3.603532	-3.213502	-2.451726
$(\log(real\_exp\_mean))^2$	0.096970	0.1271259	0.142587	0.158457	0.188480
$\log(gini)$	-0.025722	-0.0193860	-0.016043	-0.012696	-0.006468
$\log(ad\_rate)$	-0.031145	-0.0263696	-0.023855	-0.021445	-0.016825
$\log(p0to4)$	0.426400	0.4497966	0.462810	0.475904	0.500586
$\log(p5to9)$	-0.128829	-0.1069783	-0.094988	-0.083395	-0.061302
$\log(p10to14)$	0.041141	0.0586457	0.067818	0.077081	0.094637
$\log(p15to19)$	0.018531	0.0313222	0.038161	0.045158	0.057768
$\log(p20to24)$	-0.039151	-0.0289730	-0.023514	-0.018085	-0.007919
$\log(p25to29)$	-0.119307	-0.1039678	-0.095831	-0.087758	-0.072983
$\log(p30to34)$	-0.142887	-0.1241204	-0.114326	-0.104661	-0.086441
$\log(p35to39)$	-0.013261	0.0007482	0.008097	0.015586	0.029082
$\log(p40to44)$	-0.054483	-0.0407710	-0.033764	-0.026832	-0.013777
$\log(p45to49)$	-0.009368	0.0040616	0.011254	0.018120	0.031315
$\log(p50to54)$	-0.015792	-0.0025089	0.004255	0.011390	0.025223
$\log(p55to59)$	-0.010739	0.0020937	0.008915	0.015616	0.028408
$\log(p60to64)$	-0.026643	-0.0148978	-0.008505	-0.001903	0.010829
$\log(p65to69)$	-0.017110	-0.0041311	0.002675	0.009274	0.021610
$\log(p70to74)$	-0.016074	-0.0031818	0.003973	0.010891	0.024674
$\log(p75to79)$	0.006818	0.0199453	0.026484	0.033122	0.046750
$\log(pover80)$	-0.026850	-0.0157913	-0.010381	-0.004849	0.005791

Table.3.3 and Table.3.4 show that the different models matches the spatial error model of Table.3.2.

$$y_t = (\iota_T \otimes W_N)\,\mu + X_{t-1}\beta + u_t \tag{3.13}$$
$$u_t = \rho\,(I_T \otimes W_N)\,u_t + \varepsilon_t \tag{3.14}$$
$$t = 1, \ldots, T \tag{3.15}$$

Table 3.5: Estimation Results: Spatial Panel Maximum Likelihood (SPML), Spatial Panel Generalized Moments (SPGM), Least Squares Dummy Variable (LSDV) and Dynamic Panel Generalized Methods of Moments (Arellano & Bond 1991[3])(DPGMM(AB)) ($n = 47$, $T = 35$, and $N = 1645$)

$\log(TFR)$	SPML	SPGM	LSDV	DPGMM(AB)
ρ	0.674254 (0.022147) ***	0.54946607		
σ_ν^2		0.00082763		
lag				0.353606 (0.037013) ***
$\log(lag(pop\_density, 1))$	-0.0163771 (0.0174095)	-0.017743 (0.015476)	0.0776786 (0.2496147)	0.485169 (0.324223)
$(\log(lag(pop\_density, 1)))^2$	0.0016538 (0.0013904)	0.0018175 (0.0012316)	0.0080262 (0.0190958)	-0.030917 (0.025209)
$\log(lag(real\_exp\_mean, 1))$	-5.7234362 (1.7326863) ***	-6.2441 (1.7248) ***	-8.1587635 (2.0155213) ***	-5.089522 (2.337559) *
$(\log(lag(real\_exp\_mean, 1)))^2$	0.2270749 (0.0685412) ***	0.24826 (0.068263) ***	0.3227035 (0.0796065) ***	0.202124 (0.092200) *
$\log(lag(gini, 1))$	0.0118918 (0.0137283)	0.014496 (0.013994)	-0.0124552 (0.0159547)	0.011498 (0.017563)
$\log(lag(ad\_rate, 1))$	-0.0360324 (0.0087634) ***	-0.031813 (0.0081342) ***	-0.0291019 (0.0168526) .	0.049324 (0.024595) *
$\log(lag(p0to4, 1))$	0.6246373 (0.0315136) ***	0.67079 (0.031383) ***	0.6306060 (0.0550940) ***	0.272078 (0.050675) ***
$\log(lag(p5to9, 1))$	0.2359812 (0.0399109) ***	0.21131 (0.040257) ***	0.0257211 (0.0621721)	0.103450 (0.051732) *

$\log(lag(p10to14,1))$	0.0467749 (0.0313585)	0.041251 (0.031855)	0.0229333 (0.0479956)	-0.091458 (0.054953) .
$\log(lag(p15to19,1))$	-0.1808072 (0.0205411) ***	-0.18262 (0.020838) ***	-0.2903170 (0.0307829) ***	-0.298755 (0.031187) ***
$\log(lag(p20to24,1))$	-0.0957044 (0.0138215) ***	-0.10322 (0.013685) ***	-0.1192106 (0.0236034) ***	-0.129304 (0.021896) ***
$\log(lag(p25to29,1))$	-0.2683597 (0.0209416) ***	-0.27073 (0.021170) ***	-0.4103448 (0.0330438) ***	-0.267500 (0.034114) ***
$\log(lag(p30to34,1))$	-0.2831767 (0.0250284) ***	-0.28320 (0.025049) ***	-0.3239812 (0.0428268) ***	-0.289960 (0.045548) ***
$\log(lag(p35to39,1))$	-0.0768934 (0.0156915) ***	-0.083393 (0.015441) ***	-0.1834299 (0.0328672) ***	-0.169882 (0.030038) ***
$\log(lag(p40to44,1))$	-0.0481813 (0.0148061) **	-0.044103 (0.014591) **	-0.0777104 (0.0301375) *	-0.061538 (0.031882) .
$\log(lag(p45to49,1))$	0.0037819 (0.0157401)	0.0088936 (0.015535)	-0.0343759 (0.0254181)	-0.061216 (0.034499) .
$\log(lag(p50to54,1))$	0.0093755 (0.0149187)	0.000045573 (0.014862)	-0.0367954 (0.0203576) .	-0.076422 (0.027751) **
$\log(lag(p55to59,1))$	0.0206318 (0.0112965) .	0.017104 (0.011299)	-0.0110085 (0.0111422)	-0.019842 (0.023959)
$\log(lag(p60to64,1))$	-0.0528298 (0.0122143) ***	-0.059268 (0.012431) ***	-0.0676346 (0.0146975) ***	-0.058528 (0.020833) **
$\log(lag(p65to69,1))$	-0.0041745 (0.0162989)	-0.0069989 (0.016680)	-0.0512689 (0.0199666) *	-0.032209 (0.020328)
$\log(lag(p70to74,1))$	0.0247657 (0.0212499)	0.016970 (0.021771)	0.0124371 (0.0196962)	-0.037297 (0.027946)
$\log(lag(p75to79,1))$	-0.1701261 (0.0213852) ***	-0.15362 (0.021546) ***	-0.1367153 (0.0244545) ***	-0.085345 (0.024770) ***
$\log(lag(pover80,1))$	0.1153499 (0.0165672) ***	0.11265 (0.015793) ***	-0.0489186 (0.0364597)	-0.149514 (0.044055) ***
$adj.R^2$			0.92753	

$. < 0.10 \quad * < 0.05 \quad ** < 0.01 \quad *** < 0.001$
Double clustered standard deviations are in parentheses.

Table.3.5 does not indicate that log(*pop_density*) and log(*gini*) with the lag have the statistical significance in the regression to log(TFR). This result is consistent with the fact that TFR has panel non-Granger causality from *gini* in Section 3.1. In short, *gini* has no impact on TFR in the viewpoint of only time-series dependence and that of only cross-sectional dependence (spacial dependence). However, *pop_density*'s effect on TFR remains unclear.

3.3.5 Results of the Panel Vector Autoregression

Holtz-Eakin et al. (1988)[27] introduced the first vector autoregressive panel model (PVAR). PVAR was extended to following stationary PVAR (3.16) with fixed effects by Sigmund & Ferstl (2019)[56]. This paper utilizes the R package developed by them and sets up with the system GMM estimator (Blundell & Bond 1998[10]).

$$y_{i,t} = \mu_i + \sum_{l=1}^{10} A_l y_{i,t-l} + \varepsilon_{i,t} \tag{3.16}$$

$$y_{i,t} = \begin{pmatrix} \log(TFR_{i,t}) \\ \log(population_{i,t}) \end{pmatrix} \tag{3.17}$$

Let $y_{i,t} \in \mathbb{R}^2$(3.16) be an 2×1 vector of endogenous variables for the ith cross-sectional unit at time t. Let $y_{i,t-l} \in \mathbb{R}^2$ be an 2×1 vector of lagged endogenous variables. Moreover, the disturbances $\varepsilon_{i,t}$ are independently and identically distributed (i.i.d.) for all i and t with $\mathbb{E}[\varepsilon_{i,t}] = 0$ and $Var[\varepsilon_{i,t}] = \Sigma_\varepsilon$. Σ_ε is a positive semidefinite matrix. μ_i is the fixed effect in the PVAR model.

Figure 3.5 shows the positive shock on TFR has significant positive effects over 20 years so that TFR can have a statistically significant persistence and the Easterlin hypothesis that higher birth rates have crowding mechanisms resulting in lower fertility rates (Macunovich & Easterlin 2018[39]) in this paper's dataset over 47 prefectures and 36 years in Japan. Conversely, the negative shock such as covid-19 will have negative effects over 20 years. We consider only ten lags in the PVAR model over 36 years dataset to analyze and deduce the inverted J-shape curve (log(TFR) on log(TFR)) in Figure 3.5. The model (3.16) does not take consideration into spatial autocorrelation.

3.4 Conclusion

Results of the spatial panel data analysis and the panel vector autoregression validate the Easterlin hypothesis and the Second Demographic Transition in Japan. *ad_rate* has negative effects on TFR in both spatial panel data models. However, the panel non-Granger causality shows *ad_rate* does not determine TFR in the non-Granger causality standpoint. This paper uses several techniques and two datasets to infer the relationship between TFR and other variables, and the results are consistent with each other. As a unique result, the relationship between log(TFR) and log(*pop_density*) has an inverted U-shape.

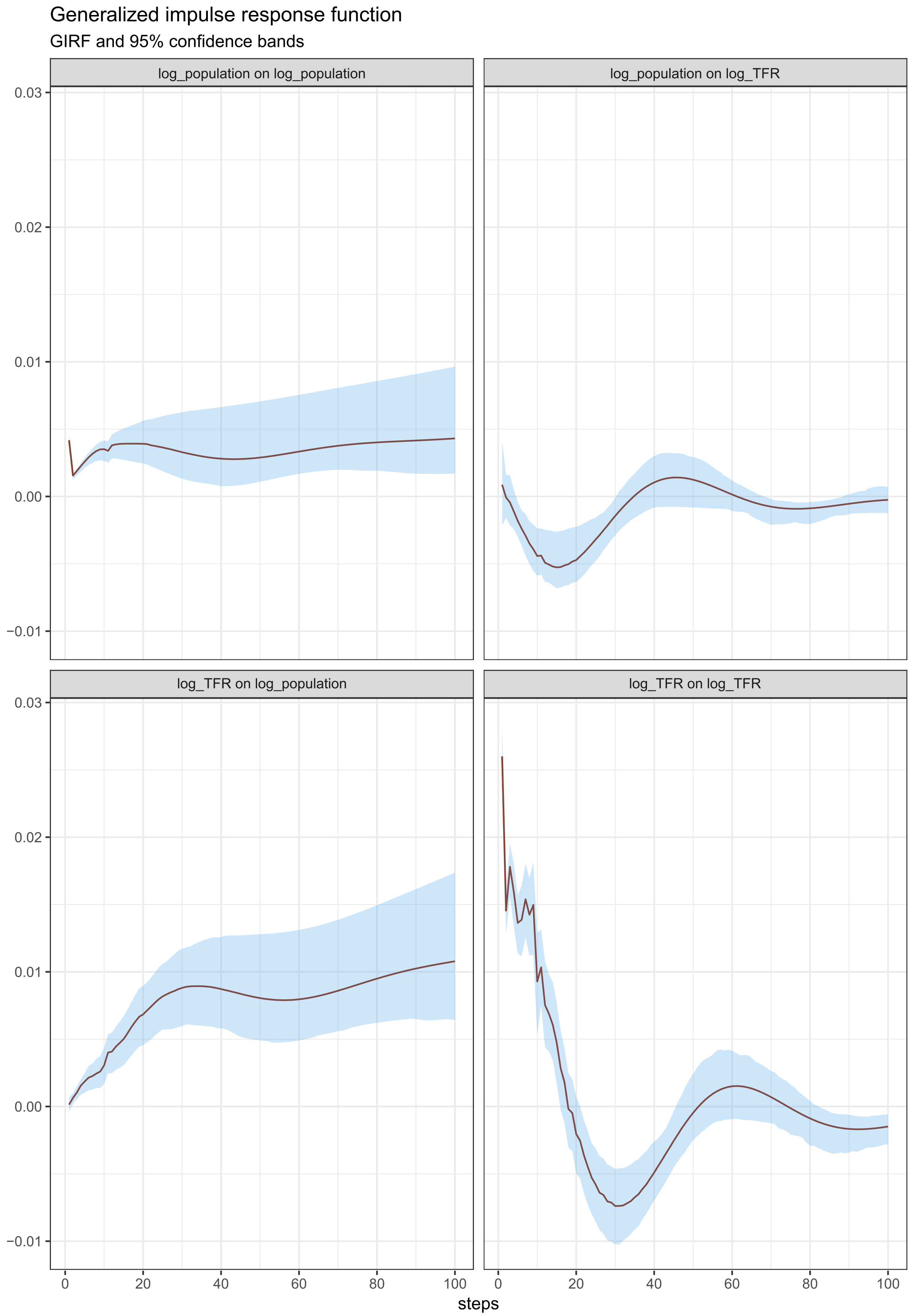

Figure 3.5: The Panel Vector Autoregression Generalized Impulse Response Function Results

Chapter 4

Crime Rates in Japan and Other Variables

4.1 Introduction

Recently, Japan has experienced the steep rise and decline of crime rates in its economic and demographic changes (Figure 4.1) since around 2000. Several papers and journalisms try to document well.

One can compare crime rates with economic inequality. One needs to research the relationship between crime rates and economic inequality and the relationship between crime rates and demography because both are not well established.

Several studies on the datasets in foreign countries cite income inequality as the determinant of crime rates. However, the relationship between crime rates and the demography is not well established. Earlier studies rely on cross-sectional data with relatively small sample sizes. Other studies have tricks of the instrumental variables to conclude the relationship.

The conventional panel analysis, such as the least square dummy variable, does not clearly show the relationships. One can utilize the characteristics of more extended time series and the geographic information in panel data Kamihigashi and I tally. The panel data analysis with the geographic characteristics suggests the demography affects the crime rates in Japan. Furthermore, economic inequality measured by the Gini index of the mean real expenditure has a positive impact on the crime rates.

4.2 The Literature and Data Characteristics

4.2.1 The Literature

The relationship between the crime rates and the socio-economic variables has been discussed for a long time.

Patterson (1991)[49] finds that absolute poverty is more strongly associated with neighborhood crime rates in 57 residential areas in 1977 in some states of the United States. He uses the percentage of households with an annual household income of less than $5,000 to measure the absolute poverty level of neighborhoods.

Chamlin and Cochran (1997)[14] use the Gini index of economic concentration as the control variable and the relative economic deprivation. Their results show that the Gini index has positive effects on crimes.

Fajnzylber et al. (2002)[25] utilize a comparative cross-country perspective. Using countries as the units of observation to study the link between inequality and crime is arguably appropriate because national borders limit the mobility of potential criminals more than neighborhood, city, or even provincial boundaries do. They conclude that an increase in income inequality has a significant and robust effect of rising crime rates. Also, the GDP growth rate has a significant crime-reducing impact. Since the rate of growth and distribution of income jointly determine the rate of poverty reduction, the two results, as mentioned above, imply that the rate of poverty alleviation has a crime-reducing effect.

Brush (2007)[12] shows that first differencing regressions found negative or insignificant coefficients for this variable, while cross-sectional regression exhibited a positive relationship between the Gini coefficient and crime rates.

Choe (2008)[16] concludes that corrected for the state-level fixed effects and first-order serial correlation, relative income inequality measured by Gini ratio seems to have a strong and robust impact on burglary. They failed to find a meaningful relationship between income inequality and other crime categories, including overall violent and property crime.

Menezes et al. (2013)[41] have an interesting result of the negative slope of the spatial correlation in their cross-sectional regressions. Thus, it can be seen that areas with low crime rates are surrounded by neighborhoods with high murder rates. One possible conclusion is that the process of urbanization may have led to the formation of islands of safety inhabited by people with higher levels of education and greater per capita income. After controlling for the other variables, we noted that inequality has a significant positive effect on criminality. However, this influence is mitigated by the coefficient of inequality to measure its influence on criminality.

The income distribution may affect crime through several channels. However, higher crime rates may affect local inequality in many factors. Enamorado et al. (2016)[24] use an instrumental variable to mitigate concerns about this form of reverse causality. They follow Boustan et al. (2013)[11] and predict the income distribution and national patterns of income growth; they then use the Gini coefficient for this predicted distribution as an instrument for the actual Gini coefficient. They conclude that increasing income inequality would be associated with lower crime rates in municipalities.

4.2.2 Data

crime_rate is from statistics of the National Police Agency in Japan and the number of violent crimes (murders, robbery, and other serious crimes) per 100,000 persons. *population* is from the Vital Statistics of Ministry of Health, Labor and Welfare in Japan. *real_exp_mean* is the mean expenditure from the Statistics Bureau of Japan's data divided by the bureau's consumer price index. Also, Kamihigashi and I calculate *age_household* and *gini* from the bureau's microdata. Three variables (*real_exp_mean*, *age_household* and *gini*) depend on data offered by the bureau. *p_young* is the proportion of the population from 15 years old to 29 years old, and *p_old* is that of the people from 65 years old or older and calculated using published data of the Vital Statistics of Ministry of Health, Labor and Welfare in Japan.

As data characteristics, one presents line plots of all regional units in Figure 4.1.

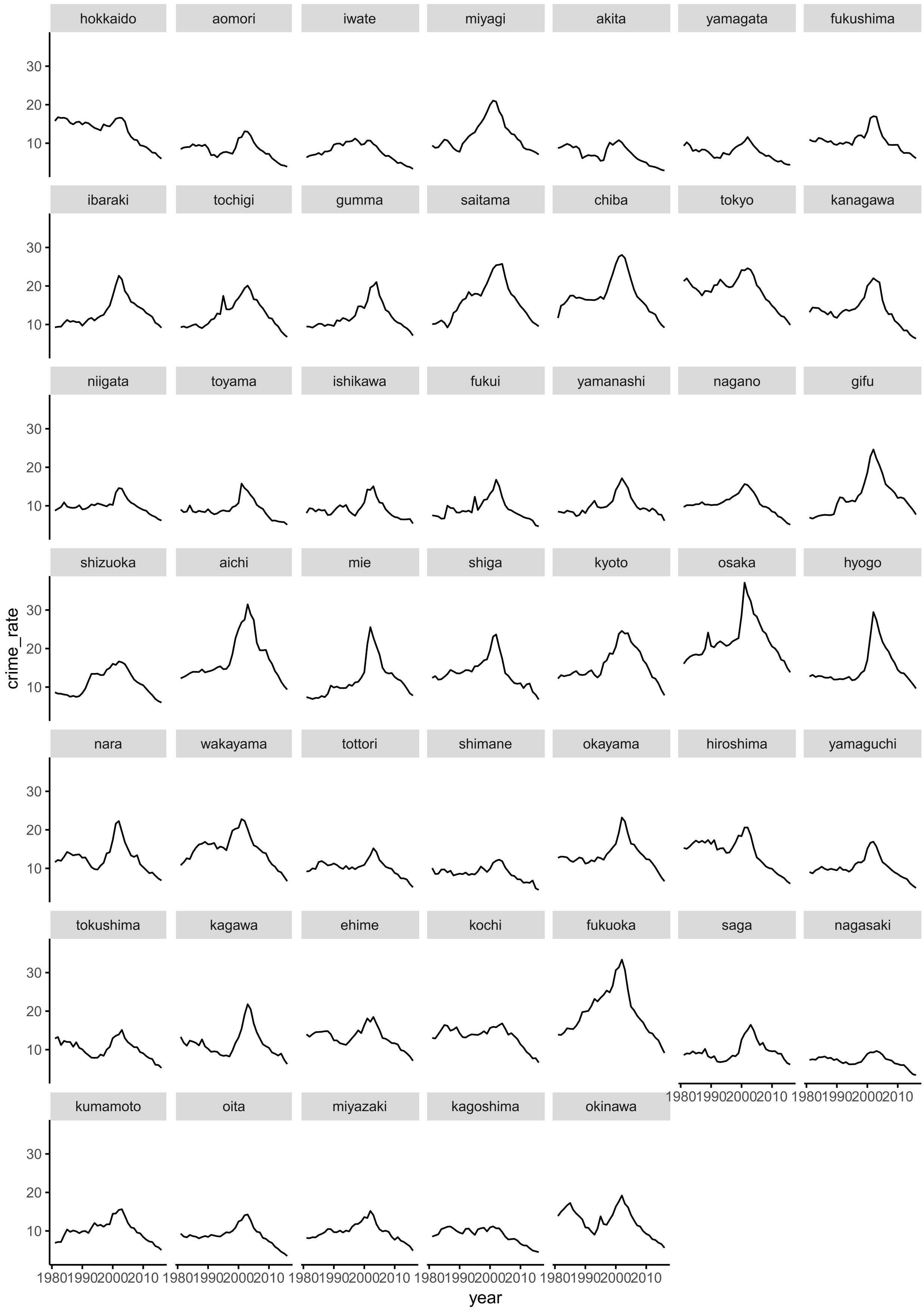

Figure 4.1: The Crime Rates

4.3 Estimation

4.3.1 The Nonparametric Regression

One puts out the nonparametric regression results to understand the relationship between *crime_rate* and other socio-economic variables. All variables are under the log-normalization to control the scaling.

Figure 4.2 shows that there are relatively strong relationships between log(*crime_rate*) vs log(*p_young*) and that between log(*crime_rate*) and log(*p_old*) has the inverted U-shape. However, the relationship between log(*crime_rate*) and log(*p_young*) is weak and spurious if other socio-economic varibles are used as the control variables as follows. The relationship between log(*crime_rate*) and log(*population*) seems to be weak and in line with the literature that the populous regions tends to have high crime rates. The relationship between log(*crime_rate*) and log(*real_exp_mean*) and that between log(*crime_rate*) and log(*gini*) are also negligible, however, valid as follows.

4.3.2 The Cross-sectional Anaysis

First, one analyzes the relationship between *crime_rate*, *pop_density*, and *gini* as only cross-sectional data to understand the statistical significance's time trends. *pop_density* is the representative variable of the demography, and *gini* is that of the economic inequality. One applies the cross-sectional Ordinary Least Square (OLS) (Equation(4.1)).

$$Y = X\beta + \varepsilon \tag{4.1}$$

Since 2000, most years have statistically significant relationships between log(*crime_rate*) and log(*gini*) in line with the cross-sectional ordinary least square (OLS). However, the significance of log(*gini*) is more apparent than the simple OLS, and its indirect effects indicate the suitability of the spatial Durbin model over OLS. The simple OLS has the bias in estimating the model of the dependent variable and the explanatory variables with spatial autocorrelations.

One sorts out some words of econometric methods in Section 4.3.2 here. The spatial autocorrelation is that the variables correlate to themselves spatially. In short, if one region has a higher crime rate, neighbor regions could tend to have higher crime rates. This situation is a positive spatial autocorrelation. If one region has a higher crime rate, neighbor regions could tend to have lower crime rates. The situation is called a negative spatial autocorrelation. *direct effects* is the impact that the variables in a region have on itself. *indirect effects* capture the recursion or the spillover in a region when its effects affect neighbor regions. *total effects* are the summations of *direct effects* and *indirect effects*.

The description as follows is based on Elhorst (2014)[23]. First, if a particular explanatory variable in a particular unit changes, not only will the dependent variable in that unit itself change but also the dependent variables in other units. The first is called a *direct effect* and the second is an *indirect effect*. Second, direct and indirect effects are different for different units in the sample. Third, indirect effects that occur if $\theta_k \neq 0$ are known as *local effects*, as opposed to indirect effects that occur if $\delta \neq 0$ and that are known as *global effects*. If both $\delta \neq 0$ and $\theta_k \neq 0$, both global and local effects occur, which cannot be separated from each other.

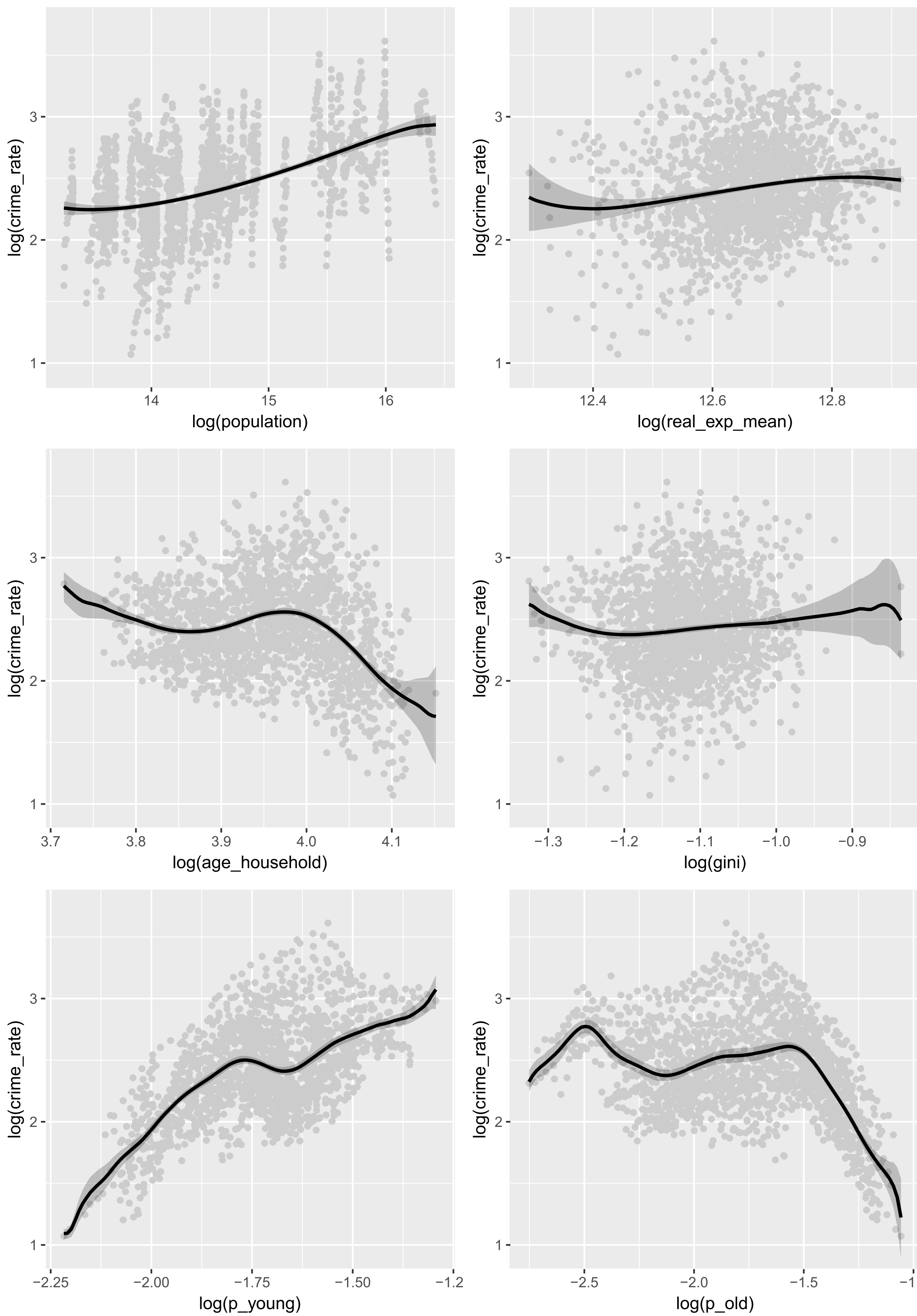

Figure 4.2: The Nonparametric Regressions

To improve the surveyability of the estimation results of spatial regression model specifications, LeSage and Pace (2009)[35] propose to report one summary indicator for the indirect effect, measured by the average of either the row sums or the column sums of the off-diagonal elements of that matrix.

W is the spatial weight matrix representing neighborhood as 1 and 0 otherwise. δWY expresses the spatial lag of Y and $WX\theta$ the spatial effects of X, respectively to control the variables' spatial autocorrelation.

$$Y = \delta WY + \alpha\iota_N + X\beta + WX\theta + \varepsilon \tag{4.2}$$
$$N = 47 \tag{4.3}$$

Figure 4.3 plot the coefficients of OLS and the Cross-sectional Spatial Dubin model's results. Each graph's band is $estimate \pm 1.96 * standard\_deviation$ and provides the sketch of the statistical significance.

Figure 4.3 shows the positive statistical significance of *gini* from around 2000. To control the spatial dependence of the dependent variable ($\log(crime\_rate)$) and the explanatry variables ($\log(population)$ and $\log(gini)$), introducing δWY and $WX\theta$ respectively provides the different result from Figure 4.3.

4.3.3 The Spatial Panel Data Analysis

Hsiao (2014)[28] presents significant advantages of panel data over cross-sectional or time-series data sets. Two points are mostly valid in the context this paper covers. First, because panel data usually give researchers a large number of data points, the inference of model parameters is more accurate. Second, the use of panel data controls the impact of omitted variables (or individual or time heterogeneity).

The dependent variable's spatial autocorrelation and the explanatory variables' one lead to the bias in the conventional Least Square Dummy Variable (LSDV). To account for the spatial autocorrelation in panel data, one can utilize the spatial panel regression. All spatial panel estimations discussed here are the fixed-effect model with some spatial lag types and time dummies.

$$Y_t = X_t\beta + \mu + \xi_t\iota_N + u_t \tag{4.4}$$
$$u_t = \rho W u_t + \varepsilon_t \tag{4.5}$$
$$\mu = (\mu_1, \ldots, \mu_N)^{\mathrm{T}} \tag{4.6}$$
$$t = 1, \ldots, T \tag{4.7}$$
$$T = 36, N = 47 \tag{4.8}$$

$$Y_t = \delta WY_t + X_t\beta + WX_t\theta + \mu + \xi_t\iota_N + \varepsilon_t \tag{4.9}$$
$$\mu = (\mu_1, \ldots, \mu_N)^{\mathrm{T}} \tag{4.10}$$
$$t = 1, \ldots, T \tag{4.11}$$
$$T = 36, N = 47 \tag{4.12}$$

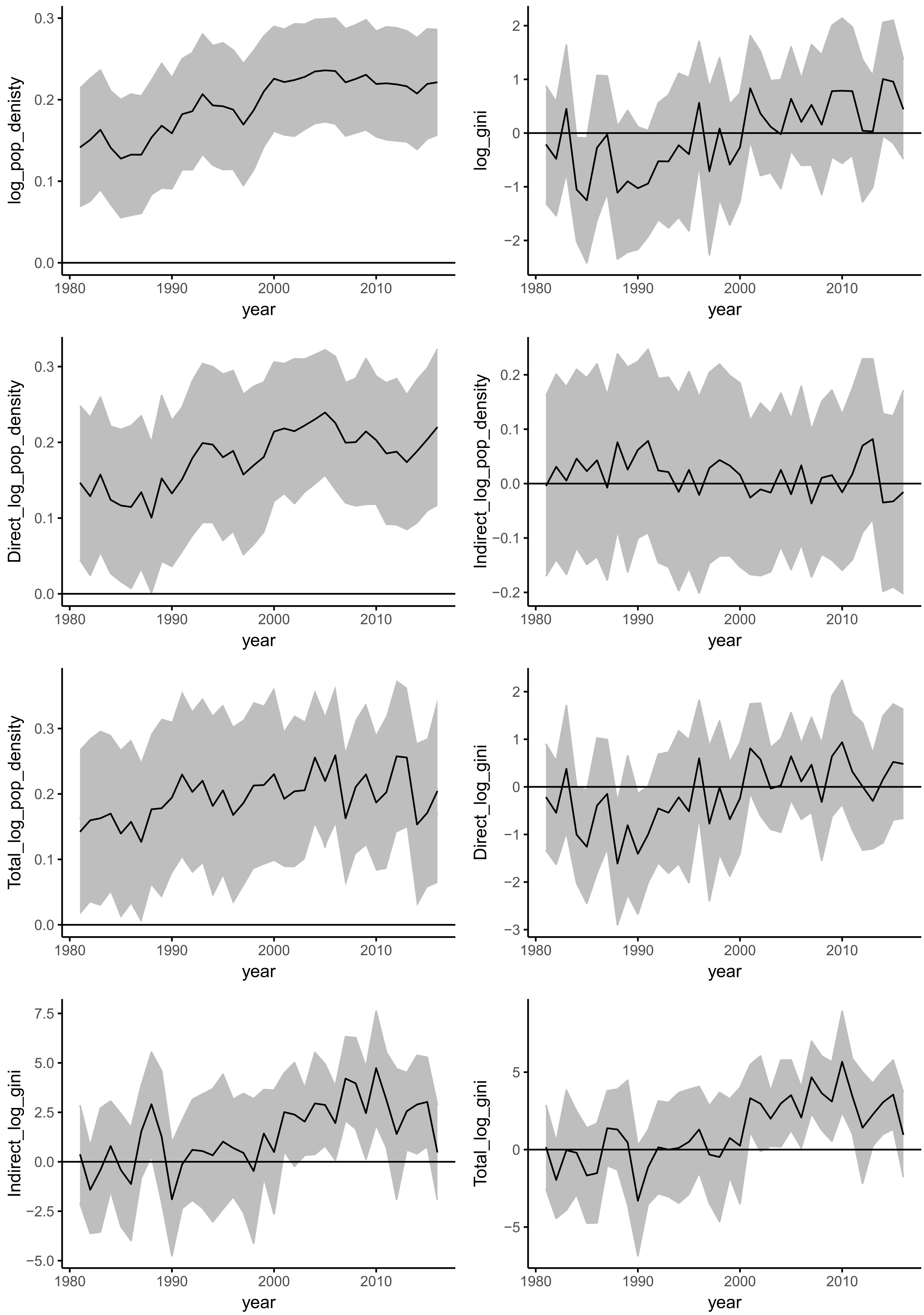

Figure 4.3: OLS & Cross-sectional Spatial Durbin Model

Table 4.1: Least Square Dummy Variable (LSDV)

	1981-1999	2000-2016	1981-2016
log(*population*)	1.863611 (0.592528)**	-0.211583 (0.376051)	1.024573 (0.390118)**
log(*gini*)	-0.046660 (0.081318)	0.165434 (0.058438)**	0.012919 (0.084648)
$Adj.R^2$	0.038514	-0.07051	0.025263

$. < 0.10 \quad * < 0.05 \quad ** < 0.01 \quad *** < 0.001$

Double clustered standard deviations are in parentheses.

Table 4.2: Spatial Panel Error Model (SPEM)

	1981-1999	2000-2016	1981-2016
ρ	-0.281137 (0.058532)***	-0.103737 (0.059762) .	-0.299921 (0.042622)***
log(*population*)	1.737719 (0.185253)***	-0.210106 (0.136480)	0.934159 (0.090994)***
log(*gini*)	-0.024640 (0.084134)	0.170220 (0.052058)**	0.024197 (0.063424)

$. < 0.10 \quad * < 0.05 \quad ** < 0.01 \quad *** < 0.001$ Standard deviations are in parentheses.

Equations(4.4)-(4.8) is refered as the Spatial Panel Error Model (SPEM) in this paper. This model can interpret the coefficients directly and accomplish smaller standard errors compared with the conventional LSDV (Table 4.1) here. Equations(4.9)-(4.12) is called the Spatial Panel Durbin Model (Table 4.5). This model can consider the spatial dependence of the dependent variable and the explanatory variables directly, however, it cannot explain the coefficients easily.

Table 4.3 and Table 4.4 show that controlling the spatial dependence is important to understand the statistically significant relationship between *crime_rate* and other socio-economic variables. The two divided data sets (1981-1999 and 2000-2016) do not result in different signs of the estimates and support the estimation based on the full term (1981-2016). The different point is that the first term (1981-1999) has the statistically significant effects of log(*p_young*) on log(*crime_rate*). This result is consistent with the nonparametric regression relationship in Figure 4.2.

This spatial panel data analysis (Equations(4.9)-(4.12)) successfully eliminates the large moves of total effects of log(*gini*) in the previous spatial Durbin model's cross-sectional analysis (Section 4.3.2), and the cross-sectional anaysis seems one neglects the spatial effects of this panel data set to estimate the effect of *gini* on *crime_rate*.

The estimation of the spatial panel Durbin model (Equations(4.9)-(4.12) and Table 4.5) is based on the Markov Chain Monte Carlo to output *direct effects*, *indirect effect*, and *total effects*, so it does not put out the estimates and the standard errors to be understand-

Table 4.3: Least Square Dummy Variable (LSDV)

	1981-1999	2000-2016	1981-2016
log(*population*)	1.593215 (0.677433)*	-0.074836 (0.383117)	1.128996 (0.459193)*
log(*real_exp_mean*)	-0.158420 (0.131994)	-0.075474 (0.087164)	-0.316815 (0.142883)*
log(*age_household*)	-0.673084 (0.285392)*	-0.352612 (0.147028)*	-0.705669 (0.216568)**
log(*gini*)	0.072669 (0.105153)	0.216149 (0.066812)**	0.197086 (0.098554)*
log(*p_young*)	0.543730 (0.473983)	0.042768 (0.285786)	0.038708 (0.367710)
log(*p_old*)	0.299154 (0.592266)	-0.178375 (0.212740)	-0.201761 (0.327273)
$Adj.R^2$	0.063256	-0.057593	0.054765

$. < 0.10 \quad * < 0.05 \quad ** < 0.01 \quad *** < 0.001$

Double clustered standard deviations are in parentheses.

Table 4.4: Spatial Panel Error Model (SPEM)

	1981-1999	2000-2016	1981-2016
ρ	-0.30452 (0.05870)***	-0.121601 (0.060038)*	-0.32078 (0.04272)***
log(*population*)	1.376582 (0.213544)***	-0.074033 (0.158820)	1.039411 (0.094873)***
log(*real_exp_mean*)	-0.163126 (0.089149).	-0.088339 (0.063718)	-0.280816 (0.063096)***
log(*age_household*)	-0.627066 (0.167839)***	-0.357124 (0.114672)**	-0.731126 (0.125043)***
log(*gini*)	0.096745 (0.089392)	0.226365 (0.056868)***	0.209118 (0.066816)**
log(*p_young*)	0.597407 (0.160374)***	0.077140 (0.170929)	0.068622 (0.120932)
log(*p_old*)	0.143913 (0.195683)	-0.178221 (0.104857).	-0.212864 (0.086944)*

$. < 0.10 \quad * < 0.05 \quad ** < 0.01 \quad *** < 0.001$ Standard deviations are in parentheses.

Table 4.5: Spatial Panel Durbin Model

1981-2016	Direct	Indirect	Total
log(*population*)	1.06269948	-0.283221705	0.77947777
log(*real_exp_mean*)	-0.28572812	0.076149851	-0.20957827
log(*age_household*)	-0.75000014	0.199883714	-0.55011642
log(*gini*)	0.20114968	-0.053608718	0.14754097
log(*p_young*)	0.03709782	-0.009886998	0.02721082
log(*p_old*)	-0.23380119	0.062310723	-0.17149047
Direct	2.5%	50%	97.5%
log(*population*)	0.87625	1.06339	1.25345
log(*real_exp_mean*)	-0.40993	-0.28659	-0.16062
log(*age_household*)	-0.99754	-0.74962	-0.49950
log(*gini*)	0.06905	0.20134	0.33458
log(*p_young*)	-0.19634	0.03628	0.27006
log(*p_old*)	-0.40499	-0.23255	-0.06205
Indirect	2.5%	50%	97.5%
log(*population*)	-0.36049	-0.281462	-0.20997
log(*real_exp_mean*)	0.04113	0.075181	0.11466
log(*age_household*)	0.12430	0.197215	0.28195
log(*gini*)	-0.09217	-0.052918	-0.01803
log(*p_young*)	-0.07364	-0.009686	0.05324
log(*p_old*)	0.01662	0.061413	0.11182
Total	2.5%	50%	97.5%
log(*population*)	0.63668	0.77929	0.93151
log(*real_exp_mean*)	-0.30245	-0.20988	-0.11767
log(*age_household*)	-0.73512	-0.54889	-0.36342
log(*gini*)	0.05095	0.14826	0.24642
log(*p_young*)	-0.14467	0.02676	0.19953
log(*p_old*)	-0.29910	-0.17031	-0.04548

able easily. Table 4.5 shows that indirect effects of log(*population*), log(*real_exp_mean*), log(*age_household*) and log(*gini*) have the opposite sign of their direct effects. In other words, the neighbor regions affect one region in the opposite direction. Table 4.4 and Table 4.5 present similar relationships, so the two different types of the spatial panel regression are robust to each other.

The demographic change in Japan tends to have decreasing *population*, *age_household* and *p_young*, and *p_old* is increasing as the results of the declining birthrate and aging population. The signs of the variables show that Japan's demographic trends contribute to its declining crime rates.

4.4 Conclusion

Considering the spatial dependence gives the statistically significant relationship between crime rates and other socio-economic variables. The demographic change in Japan affects crime rates, and economic inequality positively relates to crime rates. As future research, the relatively short term could lead to different results, and the more massive cross-sectional panel data might present more precise dynamics of crime rates and other socio-economic variables.

Chapter 5

Discussion and Conclusion

5.1 Discussion

Economic inequality has entanglements with other socio-economic variables. At first, the focus is on the relationship between economic inequality and trade openness. In Chapter 2, one gives a hint of the impact of economic inequality on trade openness. Second, Chapter 3 researches the relationship between total fertility rates (TFRs). Gini index (the economic inequality measure) has a negative statistical significance on TFRs. Third, Chapter 4 features whether the Gini index (the same data as Chapter 3) has a statistical significance on crime rates. The Gini index has a positive statistical relationship with crime rates.

5.2 Limitation of the Study

At first, the usage of income brackets as the economic inequality measure is rare in the literature. Second, the Gini index one uses in this study has a large variability to estimate. Third, The survey of crime rates and economic inequality has a large amount of literature. In Chapters 3 and 4, one relies on geographical information, so this method cannot apply to microdata. Because most microdata has no geographical information to allow the spatial econometric regression, this study's procedure is so tricky that one cannot apply to all data types such as balanced panel data.

5.3 Conclusion

Though this study has a limitation, this thesis untangles the connection between economic inequality and other socio-economic variables. Chapter 2 focuses on trade openness, Chapter 3 on total fertility rates, Chapter 4 on crime rates.

This doctoral thesis's most important results are concerning total fertility rates. The relationship between total fertility rates and population density is spurious, and the Gini index does not affect fertility rates.

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