Road infrastructure and TFP in Japan after the rapid growth period: A non-stationary panel approach

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Abstract

This study investigates the relationship between road infrastructure capital stock and total factor productivity (TFP) in Japan using the R-JIP 2017 database, allowing us to estimate TFP by considering the input quality. Using the growth accounting method, we estimate the TFP of each industry in each prefecture from 1972 to 2012 and conduct a panel data analysis to explain the TFP by road capital stock. The second-generation panel unit-root test results indicate the possibility of unit roots in road capital stock. Therefore, we use a panel autoregressive distributed lag model, considering non-stationarity and the specific type of reverse causality. The empirical analysis results show that the elasticity of aggregate TFP to road stock is 0.05 and has positive effects for 11 out of 18 industries, even after the period of rapid economic growth. In particular, the effect of infrastructure tends to be positive during periods of increased value added and TFP. The strongest impact is found for the transport equipment sector, followed by government services, transport, and communications. Furthermore, we find that the two-way fixed effects model and the first-difference estimates could produce misleading results.

Keywords:
Total factor productivity; R-JIP; Road infrastructure; Panel autoregressive distributed lag model, Non-stationarity

JEL: R11; R40; R42

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1. Introduction

Productivity growth in the U.S. has been sluggish since the early 1970s, and many economists have examined the causes of this productivity paradox (Holtz-Eakin and Schwartz, 1995). Aschauer (1989) argues that a delay in infrastructure development could answer the productivity paradox. Since this argument has been linked to expansionary fiscal policies, it has attracted the attention of economists and has led to studies on the effects of public infrastructure capital on economic outcomes or productivity using different methods, datasets, and countries (Munnell, 1992; Romp and Haan, 2007; Banerjee et al., 2020; Zhang and Cheng, 2023).

More empirical studies have employed a causal inference framework to control for endogeneity, as microdata have become more available (Duranton 2012; Baum-Snow et al. al, 2017; 2020; Magazzino and Maltese, 2021). Nevertheless, many situations compel us to rely on aggregate data, which is the focus of this study. When the explanatory variables are monetary measures of infrastructure and are given as continuous rather than dichotomous treatment variables (with/without), difference-in-differences estimators are difficult to define and not readily available (Callaway et al, 2024). Hence, a two-way-fixed effects (2FE) model is typically used for the empirical investigation. de Chaisemartin and D'Haultfœuille (2023) find that 26 of the 100 most cited papers published by the *American Economic Review* from 2015 to 2019 estimate such regressions.

Calderón et al. (2015) note that much of the empirical literature is subject to major caveats. First, studies based on time series often ignore the non-stationarity of aggregate output and infrastructure capital, leading to spurious correlations. When the time length of the panel is long, as in our case, the time-series aspect of the data must not be ignored to avoid spurious regression (Canning and Pedroni, 2008; Eberhardt and Teal, 2011). Second, empirical studies often ignore the potential simultaneity between infrastructure and economic outcomes. Although, considering this problem using instrumental variables (IVs) is common, finding appropriate IVs in long-term panel settings is difficult.

This study adds to the growing body of literature on infrastructure capital's contribution to aggregate productivity with a Japanese case study. Specifically, this study analyzes the relationship between road stock in monetary terms and total factor productivity (TFP) using the 2017 Japan Industrial Productivity (R-JIP 2017) database (Tokui et al., 2013; 2019). Using Hulten et al.'s (2006) growth accounting method and our panel data set, we estimate the TFP for each industry in each prefecture from 1972 to 2012. Then, we conduct a panel data analysis to explain the estimated TFP by road stock. The novel features of this study are as follows:

1) We estimate TFP based on Hulten et al.'s (2006) growth accounting framework and thereby derive estimates without specifying the functional form of a production function.
2) We analyze by industry over a long period of time (1972-2012)—the period after the high economic growth period (1954- 1973). The case after the rapid economic growth may be of help for developing countries.
3) We explicitly consider the possible existence of unit roots in the road infrastructure stock and TFP panel data, and thus attempt to eliminate spurious correlation.
4) We mitigate endogeneity concerns in terms of potential simultaneity (i.e., reverse causality).
5) We empirically analyze each industry (sector).

This second-generation panel unit root test results indicate the existence of unit roots in the road infrastructure stock and TFP of some sectors. Hence, unlike most previous studies, we use a panel autoregressive distributed lag (ARDL) model, which considers the non-stationarity of variables, for our empirical investigation. The use of the panel ARDL model could provide an additional advantage. As shown in Pesaran and Shin (1999), we can consider a specific type of reverse causality, such that road investment is influenced by past road capital stock and past TFP growth rates, using the ARDL model with a sufficient lag of dependent and independent variables.

The remainder of this paper is organized as follows. Section 2 reviews existing literature on infrastructure and economic growth. Section 3 describes the empirical model used in this study. Section 4 presents the panel dataset and the empirical results. Finally, Section 5 concludes the study.

2. Literature review

In the 1950s, the neoclassical theory of economic growth comes from the Solow-Swan model developed by Solow (1956) and Swan (1956). The Solow-Swan model is characterized by exogenously determined technological progress and savings rate. The endogenization of the savings rate is solved by Cass (1965) and Koopmans (1965), who advanced the research of Ramsey (1928), by Kydland and Prescott (1982), who developed the real business cycle (RBC) theory, and by Kydland and Prescott (1982), who introduced the dynamic stochastic general equilibrium (DSGE). Romer (1986) and Lucas (1988) develop the endogenization of technological progress as a theory of endogenous economic growth, which expresses sustained economic growth by modeling the process of accumulation of knowledge, human capital, social infrastructure, and R&D. As the development of the endogenous growth theory is based on whether the disparity in economic growth rates among regions or countries would converge, which is closely related to development economics, many studies focus on the role of infrastructure as the engine of economic development.

Barro (1990) is the first to explicitly include the public sector in the endogenous economic growth model. In the model, the government finances spending with income taxes while being included in the private sector's production function as a public good. Using this model, Barro (1990) shows that the maximization of the economic growth rate coincides with the maximization of the welfare level of a representative individual. Futagami et al. (1993) modify Barro's (1990) model, arguing that the stock of public capital, rather than the flow of capital, should contribute to private production. They show that the tax rate that maximizes the welfare of a representative individual is lower than the rate that maximizes the economic growth. Both Barro (1990) and Futagami et al. (1993) explicitly incorporate public sector activities into their models and analyze their relationship with economic growth. They support Aschauer (1989) and focus on the role played by infrastructure in economic growth. In fact, a mutual relationship may exist, including citations of Aschauer (1989) and Barro (1990).

Aschauer (1989) examines the relationship between aggregate productivity and stock-flow government spending variables and finds that 1) non-military public capital stock is significantly more important in determining productivity than the flow of non-military and military spending, 2) the relationship between military capital and productivity is weak, and 3) "core" infrastructure such as roads, highways, airports, transportation, sewerage, and water supply explains productivity the most. Furthermore, Aschauer (1989) argues that the delayed development of public capital stock caused the slowdown in production growth in the U.S. in the early 1970s. Munnell (1992) counters the three major criticisms on infrastructure and economic growth since Aschauer (1989). The following criticisms deserve attention because they are often raised, even at present:

1) The existence of spurious correlations is due to common trends between the output and social infrastructure data.
2) Many studies differ in their estimates of the coefficients that represent the impact of infrastructure on output.
3) The existence of reverse causality from output to social infrastructure.

However, the first difference (FD) method for non-stationary time-series data destroys the long-run equilibrium relationship. This study estimates the long-term relationship while avoiding first differences using non-stationary panel testing and estimation methods that have been developed in recent years.

Although Aschauer (1989) has often been regarded as the first to study infrastructure and productivity, Hulten and Schwab (1984) have conducted a regional study of U.S. manufacturing industries earlier. They are the first to link prior separate studies on the relationship between infrastructure deterioration, urban environmental degradation, the economic performance of aging capital stock in the snowbelt region of the U.S. and the slowdown in overall U.S. productivity growth from the 1970s to the 1980s. They show that the TFP growth rate is higher in the snowbelt region (1.80) than in the sun belt region (1.61), refuting the hypothesis that the slowdown in economic growth in the snowbelt region is due to a slowdown in productivity growth caused by deteriorating infrastructure. In addition, they argue that the growth rate of labor productivity is almost the same in the snowbelt and sunbelt regions, further supporting this result. Their results precede those of Aschauer (1989), who find a positive effect of infrastructure on economic growth; however, they represent an important rebuttal. Thus, the estimates of the impact of infrastructure on economic output and growth in earlier studies vary in terms of both sign and magnitude. Among recent meta-analyses, Melo et al. (2013), who focus on transportation infrastructure, find that the productivity effect of transport is higher in the U.S. than in European countries, while Elburz et al. (2013) find that U.S. studies are more likely to find the negative impact of infrastructure on growth. Thus, the conclusions of recent meta-analyses are inconsistent.

However, Munnell (1992) disputes this typical view that "no consensus has yet been reached" and argues that the large discrepancy in the estimated coefficients does not negate the positive impact of infrastructure on production, given that most public capital have little contribution to production, such as environmental measures or quality of life improvements. In addition, Munnell (1992) points out that the variation in the estimated coefficients is mainly a result of the fact that the effect of infrastructure decreases as the unit of observation in the comparison studies decreases, from national to state and from state to city, and a relatively uniform positive effect is observed when the spatial unit is controlled. In other words, all the payoffs for infrastructure investment cannot be captured by focusing on a small geographic area. This view is supported by Holmgren and Merkel's (2017)[2] results, in which the coefficient of the region dummy variable, 1 in the case of regional disaggregation of data and 0 otherwise, is 0.0808 (p =0.012). Melo et al. (2013) and Elburz et al. (2013) report similar results. Venables et al. (2014) highlight the importance of spatial units in the analysis of the relationship between infrastructure and economic growth.

Furthermore, Baird (2005) finds that highways have local negative spillover effects arising from economic activities being drawn to infrastructure-rich locations at the expense of adjacent areas. Several recent studies quantify these spillover effects. For example, Deng

[2] With heteroscedasticity-robust standard errors.

(2013) points out that the variation in effects in previous studies can be explained not only by differences in spatial units but also by differences in contexts, including spatial units (e.g., stage of development of the subject and the time period), differences in measurement units (e.g., industrial divisions), differences in the type and quality of infrastructure, and differences in modeling methods. Accumulating case study analyses using standard datasets such as R-JIP can clarify these points.

Utilizing instrumental variables or exogenous shocks could be considered (Kawaguchi et al., 2009). It can also be dealt with using other econometric models, such as vector autoregression (VAR) (Kawakami and Doi, 2004), difference generalized method of moments (difference GMM) (Na et al., 2013), system GMM (Barzin et al., 2018), and dynamic ordinary least squares (Okubo, 2008). Nevertheless, Munnell (1992) argues that reverse causality is unnecessarily a major problem in the estimation of coefficients. However, this argument may have changed over time. For example, preferential investment in less-developed regions can cause reverse causality. The ARDL model used in this study can consider this type of reverse causality by introducing sufficient lag terms for the dependent and independent variables (Pesaran and Shin, 1999).

While many empirical studies on infrastructure and economic growth/outcomes have focused on the U.S. and Europe, the literature focusing on Asia has increased in recent years (Banerjee et al., 2020; Magazzino and Maltese, 2021; Wan et al., 2024). We focus on studies conducted in Japan[3]. In Japan, empirical studies on this topic have been conducted intensively, particularly during the 1990s and the 2000s[4]. Mera (1973) divides the entire country into nine regions and the social infrastructure into four sectors, covers the 1954-1963, and examines the productivity effects of social infrastructure according to the primary, secondary, and tertiary sectors. Mera (1973) demonstrates that the productivity effect of social infrastructure is positive in all sectors. Miyara and Fukushige (2008) use a Cobb-Douglas production function to examine the productivity of public infrastructure per prefecture from 1976 to 1997. They suggest that the productivity of public infrastructure differs between prefectures, and that transportation contributes to production in prefectures with many large establishments, whereas congestion reduces transportation productivity. Furthermore, they reveal that water systems and telecommunications contribute to the production of secondary industries. Tsukai and Kobayashi (2009) measure infrastructure productivity with lasting effects for the future. They formulate a production function with a long persistent effect using an autoregressive fractionally integrated moving averaged (ARFIMAX) model with exogenous variables, and the model is applied to measure infrastructure productivity in Japan from 1965 to 1998. The estimated model shows a positive and significant long-term persistent effect for infrastructure. Nakagishi and Yoshino (2016) examine the productivity of public capital between 1975 and 2010 using a translog production function for each prefecture grouped by region. They find that, in secondary and tertiary industries, the productivity effect of public capital has been significantly positive throughout the estimated period and has been present in recent years. Miyagawa et al. (2013) conduct a study using R-JIP and observe the productivity effect of public capital, particularly after the collapse of the bubble economy[5]. However, they focus on a regional analysis and not on a detailed sectoral analysis.

[3] For studies on the relationship between infrastructure and economic outcome and growth using aggregated data at the macro level, see the reviews of Straub (2011) and Välilä (2020). If microdata can be used, various productivity growth rate decomposition methods can be applied (e.g. Petrin and Levinsohn, 2012); however, obtaining microdata remains a challenge, and this study uses macro level aggregated data (R-JIP). Unlike microdata, which is $N >> T$ (N is the number of units and T is the number of time points), it is important to consider non-stationarity in macro data (Baltagi, 2005).

[4] Most of them have been published in Japanese domestic journals and are detailed by Ejiri et al. (2001).

[5] The collapse of the bubble economy is often considered to be the recessionary period, lasting from March 1991 to October 1993.

This study has several contributions to the existing literature. By estimating TFP based on Hulten et al.'s (2006) growth accounting framework, we estimate the infrastructure effects without specifying the functional form of the production function. In addition, we analyze the effect of infrastructure by industry from 1973 to 2012, which roughly corresponds to the period after Japan's rapid economic growth. The long-run empirical analysis allows for the application of a panel time-series approach that can estimate long-term impacts and explicitly account for non-stationarity issues. Aside from Okubo (2008), Japanese researchers do not consider non-stationarity. As panel data can be regarded as an extension of time-series data, spurious correlations must be handled based on statistical tests, as in the case of time-series analysis (Baltagi, 2005). This study uses the panel ARDL model as the empirical model, which is generic in the sense that it can be used even when I(0): integrated variables of order zero and I(1): integrated variables of order one are mixed (Pesaran et al., 2001). We show that using the 2FE model, which does not consider the non-stationarity of the road infrastructure stock, can lead to misleading results.

Our literature review reveals the existence of several studies on the relationship between infrastructure and economic outcomes using the ARDL model (Calderón et al., 2015; Alam et al., 2020; Khanna and Sharma, 2021; Ciccarelli et al., 2021). Using balanced panel data comprising annual information on output, physical capital, human capital, and infrastructure capital for 88 industrial and developing countries from 1960 to 2000, Calderón et al. (2015) estimate the long-run elasticity of output with respect to a synthetic infrastructure index and observe that it ranges from 0.07 to 0.10. Alam et al. (2020) find that transport infrastructure has a long-run positive impact on economic development in Pakistan. Khanna and Sharma (2021) test the effects of public infrastructure on the TFP of the Indian manufacturing industry. They use an ARDL model with a cross-sectionally augmented pooled mean group (PMG) estimator to estimate the productivity effects of infrastructure and confirm the positive and significant effect of infrastructure on manufacturing productivity. Ciccarelli et al. 's (2021) analysis is based on a unique historical dataset with annual 1861–1913 data on regional railway endowments and manufacturing value added at 1911 prices. They use a panel ARDL model and find that the contribution of early railway developments to industrial growth is relatively modest when evaluated at the national level.

3. The Model

This study uses Hulten et al.'s (2006) method to analyze productivity through growth accounting using industry- and region-specific data. This method builds upon the work of Hulten and Schwab (1984), who perform a similar verification using a U.S. dataset. They show that increases in roads and electricity generation explain approximately half of productivity growth. They explicitly link infrastructure and productivity growth in the context of growth accounting. We subsequently outline Hulten et al.'s (2006) model.

3.1. Infrastructure and Production Functions

We consider the following format for the production function in a given industry:

$$Q_{i,t} = A(B_{i,t}, t)F_i\left(K_{i,t}, L_{i,t}, M(B_{i,t})\right); \tag{1}$$

where i is the region index; t is the time (year) index; $Q_{i,t}$ is the total output; $A(B_{i,t}, t)$ is Hicks-neutral technical change; $B_{i,t}$ represents the infrastructure stock; $K_{i,t}$ represents the private capital stock; $L_{i,t}$ is the labor input; and $M(B_{i,t})$ represents the intermediate inputs (the industry index is omitted to avoid complicating the equation). Here, the infrastructure stock $B_{i,t}$ influences production through two channels: the effect on output through intermediate inputs $M(B_{i,t})$ and the effect on production through the term $A(B_{i,t}, t)$ expressing the Hicks-neutral technical change. As discussed by Gibbons and Overman (2009), compared to $M(B_{i,t})$, the effect of $B_{i,t}$ on $A(B_{i,t}, t)$ is often unclear. The effect through $M(B_{i,t})$ is the straightforward effect of reducing logistics costs (called the market-mediated effect by Hulten et al. (2006)), and the effect through $A(B_{i,t}, t)$ is due to factors such as the geographical relocation of firms and changes in industrial structure (when i is a regional unit and not a company unit) adding to pure productivity growth (called the indirect effect by Hulten et al. (2006)). Although vigorous efforts are made in areas such as quantitative spatial economics to isolate the impact of pure productivity growth (Redding and Rossi-Hansberg, 2017), isolation requires firm-level microdata, for which the bar to obtain remains high in many countries, including Japan.

Assuming multiplicative structure $A_{i,0}e^{\lambda_i t}B_{i,t}^{\gamma}$ for the term $A(B_{i,t}, t)$ expressing Hicks-neutral technical change, Eq. (1) can be expressed as follows:

$$Q_{i,t} = A_{i,0}e^{\lambda_i t}B_{i,t}^{\gamma}F_i\left(K_{i,t}, L_{i,t}, M(B_{i,t})\right); \tag{2}$$

where $A_{i,0}$ is productivity in the base year, $e^{\lambda_i t}$ is a time trend term, and $B_{i,t}^{\gamma}$ represents the infrastructure stock term.

This study focuses on the parameter γ related to the infrastructure stock $B_{i,t}$. Following Solow (1957), Hulten et al. (2006), estimate γ via growth rate estimation of productivity. In Eq. (1), the term expressing productivity is $A(B_{i,t}, t)$, which is computed as the ratio of total output $Q_{i,t}$ to the inputs used to produce that output $F_i\left(K_{i,t}, L_{i,t}, M(B_{i,t})\right)$. Unlike Solow (1957), since F_i includes intermediate inputs, we use this ratio as a measure of total productivity (TP), which can be defined as $\mathrm{TP}_{i,t} \equiv Q_{i,t}/F_i\left(K_{i,t}, L_{i,t}, M(B_{i,t})\right)$. In Eq. (2), $\mathrm{TP}_{i,t} = A_{i,0}e^{\lambda_i t}B_{i,t}^{\gamma}$.

Next, we consider the rate of change of $\mathrm{TP}_{i,t}$. The data used for estimation are discrete; however, we assume that continuous data are available and consider discretization as an approximation. If we consider the natural logarithm of both sides of Eq. (1) and differentiate it with respect to variable t, the equation can be rewritten as follows:

$$\frac{\dot{Q}_{i,t}}{Q_{i,t}} = \frac{\dot{A}(B_{i,t},t)}{A(B_{i,t},t)} + \frac{\frac{\partial F_i}{\partial K_{i,t}}K_{i,t}}{F_i}\frac{\dot{K}_{i,t}}{K_{i,t}} + \frac{\frac{\partial F_i}{\partial L_{i,t}}L_{i,t}}{F_i}\frac{\dot{L}_{i,t}}{L_{i,t}} + \frac{\frac{\partial F_i}{\partial M(B_{i,t})}M(B_{i,t})}{F_i}\frac{\dot{M}(B_{i,t})}{M(B_{i,t})}; \tag{3}$$

where $\dot{A}(B_{i,t}, t) = \frac{dA(B_{i,t},t)}{dt}$; $\dot{K}_{i,t} = dK/dt$; $\dot{L}_{i,t} = dL/dt$; $and\ \dot{M}(B_{i,t}) = dM(B_{i,t})/dt$. In addition, the function $F_i(\cdot)$ is sufficiently smooth and all variables are assumed to be sufficiently smooth for t. To estimate the $\frac{\dot{A}(B_{i,t},t)}{A(B_{i,t},t)}$ term, we assume that each firm acts in the factor of production market with price as a given (Price Taker assumption). In addition, $F_i(\cdot)$ is assumed to be first-order and linearly homogenous with respect to the argument.

$$F_i\left(K_{i,t}, L_{i,t}, M\left(B_{i,t}\right)\right) = \frac{\partial F_i}{\partial K_{i,t}} K_{i,t} + \frac{\partial F_i}{\partial L_{i,t}} L_{i,t} + \frac{\partial F_i}{\partial M\left(B_{i,t}\right)} M\left(B_{i,t}\right). \tag{4}$$

Assuming that the costs of the production factors K, L, and M are p_K, p_L, and p_M, respectively, they can be written as follows from the minimization conditions of the total cost $p_K K_{i,t} + p_L L_{i,t} + p_M M\left(B_{i,t}\right)$.

$$\frac{p_K}{\frac{\partial Q_{i,t}}{\partial K_{i,t}}} = \frac{p_L}{\frac{\partial Q_{i,t}}{\partial L_{i,t}}} = \frac{p_M}{\frac{\partial Q_{i,t}}{\partial M\left(B_{i,t}\right)}}. \tag{5}$$

By substituting Eq. (5) into Eq. (3), we obtain

$$\frac{\dot{A}\left(B_{i,t},t\right)}{A\left(B_{i,t},t\right)} = \frac{\dot{Q}_{i,t}}{Q_{i,t}} - \pi_{K_{i,t}}\frac{\dot{K}_{i,t}}{K_{i,t}} - \pi_{L_{i,t}}\frac{\dot{L}_{i,t}}{L_{i,t}} - \pi_{M_{i,t}}\frac{\dot{M}\left(B_{i,t}\right)}{M\left(B_{i,t}\right)}, \tag{6}$$

provided that $\pi_{K_{i,t}} = \frac{p_K K_{i,t}}{p_K K_{i,t}+p_L L_{i,t}+p_M M\left(B_{i,t}\right)}$; $\pi_{L_{i,t}} = \frac{p_L L_{i,t}}{p_K K_{i,t}+p_L L_{i,t}+p_M M\left(B_{i,t}\right)}$; $\pi_{M_{i,t}} = \frac{p_M M\left(B_{i,t}\right)}{p_K K_{i,t}+p_L L_{i,t}+p_M M\left(B_{i,t}\right)}$.

The discretization procedure for Eq. (6) is then explained. To calculate the TP (or TFP) using the growth accounting method, the TP using a discrete set of data, such as annual data, must be estimated. Therefore, the term expressed using the derivative of t in Eq. (6) can be approximated using the difference. In addition, $\pi_{K_{i,t}}$, $\pi_{L_{i,t}}$, $\pi_{M_{i,t}}$ which represents the cost share of each production factor, is discretely approximated using the average value of the cost share of the previous period and the cost share of the current period. This can be written as:

$$\Delta\ln\left(A\left(B_{i,t},t\right)\right) = \Delta\ln(Q_{i,t}) - \bar{\pi}_K\Delta\ln(K_{i,t}) - \bar{\pi}_L\Delta\ln(L_{i,t}) - \bar{\pi}_M\Delta\ln\left(M\left(B_{i,t}\right)\right); \tag{7}$$

provided that

$$\begin{aligned}
\Delta\ln(A\left(B_{i,t},t\right)) &= \ln\left(A\left(B_{i,t},t\right)\right) - \ln\left(A\left(B_{i,t-1},t-1\right)\right);\\
\Delta\ln(Q_{i,t}) &= \ln\left(Q_{i,t}\right) - \ln\left(Q_{i,t-1}\right);\\
\Delta\ln(K_{i,t}) &= \ln\left(K_{i,t}\right) - \ln\left(K_{i,t-1}\right);\\
\Delta\ln(L_{i,t}) &= \ln\left(L_{i,t}\right) - \ln\left(L_{i,t-1}\right);\\
\Delta\ln(M\left(B_{i,t}\right)) &= \ln(M\left(B_{i,t}\right)) - \ln(M\left(B_{i,t-1}\right));\\
\bar{\pi}_{K_{i,t}} &= \frac{\pi_{K_{i,t}} + \pi_{K_{i,t-1}}}{2};\\
\bar{\pi}_{L_{i,t}} &= \frac{\pi_{L_{i,t}} + \pi_{L_{i,t-1}}}{2};\\
\bar{\pi}_{M_{i,t}} &= \frac{\pi_{M_{i,t}} + \pi_{M_{i,t-1}}}{2}.
\end{aligned}$$

3.2. Estimation of TP

We consider the estimation of $\mathrm{TP}_{i,t}$. The variables on the right-hand side of Eq. (7) are observable from statistical data. By calculating the right-hand side, we obtain $\Delta\ln(\mathrm{TP}_{i,t})$ as:

$$\Delta\ln(\mathrm{TP}_{i,t}) = \ln(\mathrm{TP}_{i,t}) - \ln(\mathrm{TP}_{\mathrm{i,t-1}}) \approx \frac{\mathrm{TP}_{i,t}-\mathrm{TP}_{i,t-1}}{\mathrm{TP}_{i,t-1}}. \tag{8}$$

Therefore, the right-hand side approximately expresses the rate of change in $\mathrm{TP}_{i,t}$. Accordingly, by setting the base year, normalizing the TP in the base year to 1, and sequentially calculating the right-hand side of Eq. (7), the time series $\{\mathrm{TP}_{i,t}\}_{t=0,1,2\dots}$ can be obtained.

3.3. Relativization of TP

If we follow the steps described in Subsections 3.1 and 3.2, we can obtain the regional TP time series $\{\mathrm{TP}_{i,t}\}_{t=0,1,2\dots}$ of an industry for each region *i*. However, we investigate how infrastructure stock contributes to the growth of TP of each industry. Accordingly, we use the $\mathrm{TP}_{i,0}$ data for the base year per region *i* and consider the relative contribution of infrastructure stock to the TP growth for each industry. We use a method based on the translog index of Jorgenson and Nishimizu (1978) and Caves et al. (1982) and perform the relativization of $\mathrm{TP}_{i,t}$. Specifically, we standardize the geometric mean TP_0^* of the base year $\mathrm{TP}_{i,0}$, and calculate $\mathrm{TP}_{i,0}$:

$$\ln\left(\frac{\mathrm{TP}_{i,0}}{\mathrm{TP}_0^*}\right) = \ln\left(\frac{Q_{i,0}}{Q_0^*}\right) - \overleftarrow{\pi}_{K_{i,0}}\ln\left(\frac{K_{i,0}}{K_0^*}\right) - \overleftarrow{\pi}_{L_{i,0}}\ln\left(\frac{L_{i,0}}{L_0^*}\right) - \overleftarrow{\pi}_{M_{i,0}}\ln\left(\frac{M(B_{i,0})}{M_0^*}\right); \tag{9}$$

provided that

$$\begin{aligned}
\ln(\mathrm{TP}_0^*) &= \frac{\sum_i\ ln\left(\mathrm{TP}_{i,0}\right)}{\#I}; \qquad \mathrm{TP}_0^* = \sqrt[\#I]{\Pi_i \mathrm{TP}_i};\\
\ln(Q_0^*) &= \frac{\sum_i\ ln\left(Q_{i,0}\right)}{\#I}; \qquad Q_0^* = \sqrt[\#I]{\Pi_i Q_i};\\
\ln(K_0^*) &= \frac{\sum_i\ ln\left(K_{i,0}\right)}{\#I}; \qquad K_0^* = \sqrt[\#I]{\Pi_i K_i};\\
\ln(L_0^*) &= \frac{\sum_i\ ln\left(L_{i,0}\right)}{\#I}; \qquad L_0^* = \sqrt[\#I]{\Pi_i L_i};\\
\ln(M_0^*) &= \frac{\sum_i\ ln\left(M\left(B_{i,0}\right)\right)}{\#I}; \qquad M_0^* = \sqrt[\#I]{\Pi_i M\left(B_{i,0}\right)};\\
\overleftarrow{\pi}_{K_{i,0}} &= \frac{\pi_{K_{i,0}} + \pi_{K_0}^*}{2}; \qquad \pi_{K_0}^* = \frac{\sum_i\ \pi_{K_{i,0}}}{\#I};\\
\overleftarrow{\pi}_{L_{i,0}} &= \frac{\pi_{L_{i,0}} + \pi_{L_0}^*}{2}; \qquad \pi_{L_0}^* = \frac{\sum_i\ \pi_{L_{i,0}}}{\#I};\\
\overleftarrow{\pi}_{M_{i,0}} &= \frac{\pi_{M_{i,0}} + \pi_{M_0}^*}{2}; \qquad \pi_{M_0}^* = \frac{\sum_i\ \pi_{M_{i,0}}}{\#I};
\end{aligned}$$

where $\#I$ expresses the total number of regions i.

3.4. Panel data analysis

In the steps described in Subsection 3.2, the $\mathrm{TP}_{i,0}$ of each region i, normalized by the national average in the base year, and the time series $\{\mathrm{TP}_{i,t}\}_{t=1,2...}$ of TP normalized by the base year in each region i, are obtained. Here, the value obtained by $\mathrm{TP}_{i,0} \times \mathrm{TP}_{i,t}$ is replaced with a new value $\mathrm{TP}_{i,t}$.

Using the TP index calculated in this way, we estimate the parameter γ of infrastructure stock using a panel data analysis, similar to Hulten et al. (2006). In Eq. (2), which assumes a multiplicative structure for the term expressing Hicks-neutral technical change, we assume that the time series on the right-hand side $\mathrm{TP}_{i,t}$ and the infrastructure stock on the left-hand side $B_{i,t}$ are known. By taking the natural logarithm of both sides of Eq. (2) and adding the error term $\nu_{i,t}$, we obtain

$$\ln(\mathrm{TP}_{i,t}) = \ln(A_{i,0}) + \lambda_i t + \gamma \ln(B_{i,t}) + \nu_{i,t}\ ; \tag{10}$$

as the estimation equation. In the analysis, $\ln(A_{i,0})$ is a constant term expressing the fixed effect of each region and $\lambda_i t$ denotes the linear time trend term.

When $\ln(\mathrm{TP}_{i,t})$ or $\ln(B_{i,t})$ is a time series that does not satisfy stationarity, it needs to be analyzed by taking the difference and making it stationary or using an econometric model. The FD method looks at the short-term effects of infrastructure investment on changes in TFP. In other words, the FD method disrupts the long-term equilibrium relationship (Munnell, 1992). If $\ln(\mathrm{TP}_{i,t})$ and $\ln(B_{i,t})$ are cointegrated in I(1), fully modified OLS (Pedroni, 2001) and dynamic OLS (Kao and Chiang, 2001) can be used (Okubo, 2008). However, a few sectors suggest I(0) or stationarity for $\ln(\mathrm{TP}_{i,t})$, as verified later in this study. The panel ARDL model can be used even when the I(0) and I(1) variables are mixed, provided that I(2) is not present (Pesaran et al., 1999, 2001).

The panel ARDL model can be formulated as follows:

$$\ln(\mathrm{TP}_{i,t}) = \ln(A_{i,0}) + \sum_{j=1}^{p} \lambda_{ij} \ln(\mathrm{TP}_{i,t-j}) + \sum_{j=0}^{q} \delta_{ij} \ln(B_{i,t-j}) + \nu_{i,t}. \tag{11}$$

If we express this as an error correction equation, then

$$\Delta\ln(\mathrm{TP}_{i,t}) = \ln(A_{i,0}) + \phi_i \left(\ln(\mathrm{TP}_{i,t-1}) - \theta_i \ln(B_{i,t})\right) + \sum_{j=1}^{p-1} \lambda_{ij}^{*} \Delta\ln(\mathrm{TP}_{i,t-j}) + \sum_{j=0}^{q-1} \delta_{ij}^{*} \Delta\ln(B_{i,t-j}) + \nu_{i,t}; \tag{12}$$

is obtained, where $\Delta\ln(\mathrm{TP}_{i,t}) = \ln(\mathrm{TP}_{i,t}) - \ln(\mathrm{TP}_{i,t-1})$; $\phi_i = -(1 - \sum_{j=1}^{p} \lambda_{ij})$; $\theta_i = \sum_{j=0}^{q} \delta_{ij}/(1 - \sum_k \lambda_{ik})$ $\lambda_{ij}^{*} = -\sum_{m=j+1}^{p} \lambda_{im}$, $j = 1, 2, ..., p-1$, and $\delta_{ij}^{*} = -\sum_{m=j+1}^{q} \delta_{im}$, $j = 1, 2, ..., q-1$. Here, ϕ_i is the error-correcting speed of adjustment term. The parameter is expected to be significantly negative under the prior assumption that the variables return to a long-term equilibrium (Blackburne III and Frank, 2007). λ_{ij}^{*} and δ_{ij}^{*} capture short-term or immediate impacts. Our main interest is θ_i, which captures the long-term or equilibrium impacts. According to Murthy and Okunade (2016), the reverse causality problem can be mitigated by estimating both the short- and long-term coefficients simultaneously and with sufficient lagged dependent and explanatory variables.

Pesaran et al. (1999) propose a PMG estimator for Eq. (12). Different from 2FE model, where only intercept differs among regions, this estimator allows the intercept, short-term coefficients, and error variances to differ across the groups but constrains the long-term coefficients from being equal across groups ($\theta_i = \theta$). They develop a maximum likelihood method to estimate the parameters[6]. Pesaran et al. (1999) show that the PMG estimator is robust to outliers and lag orders[7]. Blackburne III and Frank (2007) note that the 2FE estimation approach produces inconsistent and potentially misleading results when slope coefficients are not identical. From the empirical side, Martínez-Zarzoso and Bengochea-Morancho (2004) show that a fixed effects estimator, which imposes homogeneity of slope while allowing only the intercepts to vary across individuals, may produce suspicious results in terms of an environmental Kuznets curve.

3.5. R-JIP

Here, we discuss the Regional-Level Japan Industrial Productivity (R-JIP) database used in this study and explain its appropriateness for analyzing productivity by industry and region. Then, we describe the features of the latest R-JIP version used in this study. Moreover, we outline the R-JIP social infrastructure data, which is another dataset used in this study.

R-JIP is a policy analysis database published by The Research Institute of Economy, Trade and Industry and is regarded as a basic resource for analyzing interregional productivity disparities and industrial structure in Japan[8]. The R-JIP consists of annual data needed to estimate the TFP of 47 prefectures and 23 industries, including capital and labor investments accounting for nominal and real added value and differences in quality. This study uses R-JIP 2017, the latest available R-JIP database. In R-JIP 2017, the available annual data period is extended from the period (1970-2009) in R-JIP 2014 to (1970-2012). Additionally, the data period extended by R-JIP 2017 includes the Great East Japan Earthquake of 2011, with the estimation of the damaged capital stock reflected in the database.

3.6. R-JIP2017

In R-JIP 2017, annual data are provided to estimate the TFP of 47 prefectures and the following 23 industries: Agriculture, forestry, and fishing; mining; food products and beverages; textiles; pulp, paper, and paper products; chemicals; petroleum and coal products; non-metallic mineral products; basic metal; fabricated metal products; machinery; electrical machinery; transport equipment; precision instruments; other manufacturing; construction; electricity, gas, and water supply; wholesale and retail; finance and insurance; real estate; transport and communications; private nonprofit services; and government services. We use data on real value added (price in 2000), nominal value added, real capital stock (price in 2000), nominal cost of capital, quality index (capital, common nationwide), man-hour (workers × total annual working hours per worker/1000), nominal labor cost, and quality index (labor). Notably, unlike the JIP database, the R-JIP database uses outputs based on gross value-added, as it does not have information on intermediate inputs owing to the limitation of available data. However, when using the output based on gross value-added, real value-added items receive a negative value. Table 1 lists these negative values. Four industries (pulp, paper, and paper

[6] Eviews 13 is used for the estimation.
[7] See Cho et al. (2022) for details about the ARDL model.
[8] https://www.rieti.go.jp/jp/database/r-jip.html (accessed on April 1, 2024)

products; petroleum and coal products; basic metals; and precision instruments) have negative real value added; thus, they are excluded from the analysis.

Table 1: Industries with negative real value added, around here

The R-JIP database provides labor quality indices for labor input, which enables us to analyze labor input by considering differences in quality. To calculate the labor quality index for each prefecture, we consider education, age, gender, and industry. We refer to Tokui et al. (2013, 2019) for details on the calculation method. The R-JIP database also provides a quality index for capital stock, which allows us to analyze capital inputs with different quality levels. For the quality of capital, we obtain the real capital stock series by industry and capital service input from the JIP database. Additionally, we obtain the capital quality index from the ratio of the two databases. Again, we refer to Tokui et al. (2013, 2019) for details on the calculation method of the capital quality index.

Moreover, the R-JIP database contains social infrastructure data. According to the summary of the R-JIP database on its website, the social infrastructure data in the R-JIP database is based on the estimation of social infrastructure stock by the Cabinet Office[9]. In the R-JIP database, similar to the nationwide JIP database, the capital stock that can be used in the production activities of each sector is calculated as the capital service input of each sector, regardless of whether the investment entity belongs to the private or the public sector. For example, in the agriculture, forestry, and fisheries sectors, many public capital improvements, such as agricultural roads and irrigation channels, are implemented. The same applies to water supply facilities in the electricity, gas, and water industries and toll roads in the transportation industry. Additionally, the service industry (public) is included in the sectoral classification, which includes schools, cultural facilities, airports, and harbors. Furthermore, cases in which regional productivity differences are considered are found, with the regional development of social infrastructure being the focus. In such cases, "social infrastructure" data defined by investment entities are often used. However, when using "social infrastructure" data defined by investment entities, combined with the R-JIP data defining capital categories according to use, some social infrastructure data could be double counted. Therefore, public capital inputs that cannot be associated with the economic activities of individual sectors, except for those already counted as capital service inputs of each sector in the R-JIP database, are referred to as "social infrastructure consistent with the R-JIP database" and are provided as ancillary data. The "social infrastructure consistent with the R-JIP database" includes roads other than toll roads, urban parks, flood control, mountain control, and coastal maintenance. In the "social infrastructure consistent with the R-JIP database," "toll roads" are classified as an input of the transportation and communication sector and are classified separately from "roads other than toll roads", which are defined as social infrastructure. Therefore, the sum of "toll roads" and "roads other than toll roads" is used as road stock data in this study.

[9] https://www5.cao.go.jp/keizai2/ioj/index.html (accessed on April 1, 2024)

4. Empirical analysis

4.1. Construction of panel datasets

We conduct an empirical analysis based on Hulten et al.'s (2006) method using the R-JIP2017 database. However, we modify the method to include real value added.

4.1.1. TFP estimation using real value added

We explain the assumptions about the production function required for the TFP estimation using R-JIP2017. Section 3 outlines a method for estimating productivity using growth accounting based on the assumption that the dataset includes both gross output and intermediate inputs. However, owing to limited data, the R-JIP database does not include information on intermediate inputs and instead uses output data based on gross value added. Hulten et al. (2006) point out that although real value added data are generally used because they are easier to obtain than gross output data, using them requires a weak separability assumption in the production function (Goldman and Uzawa, 1964) and that using gross output data is preferable. However, studies using real value added are widely conducted because of the availability of data. Hulten et al. (2006) conduct an analysis using real value-added to enable a comparison with those studies. Hulten and Schwab (1984) and Hulten et al. (2006) assume that the production function is weakly separable into value added and intermediate inputs, and that Hicks-neutral technical change is included in the value added function. In this sense, TP in Section 3 is synonymous with TFP in this study. The deflator common to all countries is used for the real value added because of the availability of data.

4.1.2. Estimating TFP by considering labor and capital quality

We explain TFP estimation by considering the quality index using R-JIP2017. The rate of increase in TFP in industry s and prefecture i at time $t, \Delta\ln\left(\mathrm{TFP}_{i,s,t}\right)$, can be obtained from the following equation:

$$\begin{aligned}&\Delta\ln\left(\mathrm{TFP}_{i,s,t}\right) = \\ &\Delta\ln(V_{i,s,t}) - \tfrac{1}{2}\left(S^K_{i,s,t} + S^K_{i,s,t-1}\right)\Delta\ln(K_{i,s,t}) - \tfrac{1}{2}\left(S^L_{i,s,t} + S^L_{i,s,t-1}\right)\Delta\ln(L_{i,s,t});\end{aligned} \tag{13}$$

where i (i = 1, ..., N) is an index indicating the prefecture; s (s=1, …, S) is an index indicating the industry; t (t=1972, ..., 2012) is an index indicating time; $V_{i,s,t}$ is the real value added; $S^K_{i,s,t}$ is the capital cost share; $S^L_{i,s,t}$ is the labor cost share; $K_{i,s,t}$ represents capital inputs; and $L_{i,s,t}$ represents the labor input. In addition, if $Q^K_{i,s,t}$ is the quality index of capital, $Q^L_{i,s,t}$ is the labor quality index, $Z_{i,s,t}$ is the real capital stock, and $H_{i,s,t}$ is man-hours, then $K_{i,s,t} = Q^K_{i,s,t}Z_{i,s,t}$; $L_{i,s,t} = Q^L_{i,s,t}H_{i,s,t}$ holds. Therefore, Eq. (13) can be rewritten as follows:

$$\begin{aligned}&\Delta\ln\left(\mathrm{TFP}_{i,s,t}\right) = \\ &\quad\Delta\ln\left(V_{i,s,t}\right) - \tfrac{1}{2}\left(S^K_{i,s,t} + S^K_{i,s,t-1}\right)\left(\Delta\ln\left(Z_{i,s,t}\right) + \Delta\ln\left(Q^K_{s,t}\right)\right) \\ &\qquad - \tfrac{1}{2}\left(S^L_{i,s,t} + S^L_{i,s,t-1}\right)\left(\Delta\ln(H_{i,s,t}) + \Delta\ln(Q^L_{i,s,t})\right),\end{aligned} \tag{14}$$

provided that the quality of capital $Q^K_{i,s,t}$ takes the same value for all prefectures i within the same industry s. Additionally, $Q^K_{s,t}$ values are available for the right-hand side of Eq.

(1). Statistical values are available for the right-hand side of Eq. (14), we obtain a time series for TFP standardized to 1 $\text{TFP}_{i,s,1972}$ for each industry s and prefecture *i*.

4.1.3. Relativization of TFP

We relativize TFP using $\text{TFP}_{i,s,1972}$ for industry *s* in each prefecture *i*. First, we denote the national geometric mean of each variable with 1972 as the base year as $\ln(\bar{V}_{s,1972}) = \frac{1}{N}\sum_{i=1}^{N}\ln(V_{i,s,1972})$ and $\ln(\bar{K}_{s,1972}) = \frac{1}{N}\sum_{i=1}^{N}\ln(K_{i,s,1972})$ and $\ln(\bar{L}_{s,1972}) = \frac{1}{N}\sum_{i=1}^{N}\ln(L_{i,s,1972})$. In addition, we denote the national arithmetic mean of the cost shares of capital and labor as $(\bar{S}_{s,1972}^{K}) = \frac{1}{N}\sum_{i=1}^{N}S_{i,s,1972}^{K}$ and $(\bar{S}_{s,1972}^{L}) = \frac{1}{N}\sum_{i=1}^{N}S_{i,s,1972}^{L}$, respectively. We standardize the geometric mean of TFP for each prefecture i and industry s in the base year $t = 1972$ to 1. Thus, $\text{TFP}_{i,s,1972}$ for each prefecture *i* can be obtained using the following equation:

$$\ln\left(\frac{TFP_{i,s,1972}}{\overline{TFP}_{s,1972}}\right) = \ln\left(\frac{V_{i,s,1972}}{\bar{V}_{s,1972}}\right) - \frac{1}{2}\left(S_{i,s,1972}^{K} + \bar{S}_{s,1972}^{K}\right)\ln\left(\frac{K_{i,s,1972}}{\bar{K}_{s,1972}}\right) - \frac{1}{2}\left(S_{i,s,1972}^{L} + \bar{S}_{s,1972}^{L}\right)\ln\left(\frac{L_{i,s,1972}}{\bar{L}_{s,1972}}\right). \quad (15)$$

Here, we denote the national mean of real capital stock, capital quality, man-hours, and labor quality as $\ln(\bar{Z}_{s,1972}) = \frac{1}{N}\sum_{i=1}^{N}\ln(Z_{i,s,1972})$, $\ln(\bar{Q}_{s,1972}^{K}) = \frac{1}{N}\sum_{i=1}^{N}\ln(Q_{i,s,1972}^{K})$, $\ln(\bar{H}_{s,1972}) = \frac{1}{N}\sum_{i=1}^{N}\ln(H_{i,s,1972})$, and $\ln(\bar{Q}_{s,1972}^{L}) = \frac{1}{N}\sum_{i=1}^{N}\ln(Q_{i,s,1972}^{L})$, respectively. Hence, $K_{i,s,1972} = Q_{i,s,1972}^{K}Z_{i,s,1972}$; $L_{i,s,1972} = Q_{i,s,1972}^{L}H_{i,s,1972}$ holds, so we substitute these into Eq. (15), and obtain the following:

$$\ln\left(\frac{TFP_{i,s,1972}}{\overline{TFP}_{s,1972}}\right) = \ln\left(\frac{V_{i,s,1972}}{\bar{V}_{s,1972}}\right) - \frac{1}{2}\left(S_{i,s,1972}^{K} + \bar{S}_{s,1972}^{K}\right)\left(\ln\left(\frac{Z_{i,s,1972}}{\bar{Z}_{s,1972}}\right) + \ln\left(\frac{Q_{i,s,1972}^{K}}{\bar{Q}_{s,1972}^{K}}\right)\right) - \frac{1}{2}\left(S_{i,s,1972}^{L} + \bar{S}_{s,1972}^{L}\right)\left(\ln\left(\frac{Z_{i,s,1972}}{\bar{Z}_{s,1972}}\right) + \ln\left(\frac{Q_{i,s,1972}^{K}}{\bar{Q}_{s,1972}^{K}}\right)\right). \quad (16)$$

Since $Q_{i,s,1972}^{K} = Q_{s,1972}^{K} \quad \forall i$, we obtain

$$\ln\left(\frac{TFP_{i,s,1972}}{\overline{TFP}_{s,1972}}\right) = \ln\left(\frac{V_{i,s,1972}}{\bar{V}_{s,1972}}\right) - \frac{1}{2}\left(S_{i,s,1972}^{K} + \bar{S}_{s,1972}^{K}\right)\ln\left(\frac{Z_{i,s,1972}}{\bar{Z}_{s,1972}}\right) - \frac{1}{2}\left(S_{i,s,1972}^{L} + \bar{S}_{s,1972}^{L}\right)\left(\ln\left(\frac{H_{i,s,1972}}{\bar{H}_{s,1972}}\right) + \ln\left(\frac{Q_{i,s,1972}^{K}}{\bar{Q}_{s,1972}^{K}}\right)\right). \quad (17)$$

From this equation, we can stipulate the TFP level ($\text{TFP}_{i,s,1972}$) for base year 1972 for each industry s and prefecture i. Thus, we can calculate $\text{TFP}_{i,s,t}$ at any other year: $t = 1973, \dots, 2012$ in industry s and prefecture i, using the sequential equation of $\varDelta\ln(\text{TFP}_{i,s,t}) = \ln(\text{TFP}_{i,s,t}) - \ln(\text{TFP}_{i,s,t-1})$.

Fig. 1 shows the change in relativized TFP (TFP index) for each industry and prefecture (grouped by region: Hokkaido, Tohoku, Kanto, Chubu, Kinki, Chugoku, Shikoku, and Kyushu). Some industries, such as the service industry, show an upward trend during the analysis period, whereas others, such as the real estate industry, show considerable deterioration. In addition, we find that the transition pattern differs among the prefectures; however, we observe a certain degree of similarity. Since Okinawa has historically exhibited a TFP level that differs considerably from that of other prefectures, we exclude Okinawa in the following analysis (i.e., $N = 46$, after excluding Okinawa).

Fig. 1 Changes in TFP index, around here

4.2. Panel data analysis

4.2.1. Overview of Panel data analysis

We conduct a panel data analysis to estimate the effect of infrastructure on TFP. The response variables used in the analysis are the time series $\mathrm{TFP}_{i,s,t}$ for the TFP of each industry and prefecture obtained using Eqs. (17) and (14), respectively. The explanatory variables are the road capital stock explained in Subsection 4.1. We compute Eq. (10) using Hulten et al.'s (2006) method. In the Indian context, Hulten et al. (2006) indicate relatively monotonic growth when looking at TFP over the long term; thus, assuming linear exogenous growth seems reasonable. However, as shown in Figure 1, considering the existence of linear exogenous growth over time in the Japanese context is difficult. The fact that the change in road stock (the sum of "toll roads" and "roads other than toll roads") in each prefecture shows a relatively monotonic increasing trend suggests that the term exogenously changing TFP with time is changing in the same way as TFP is highly likely.

Therefore, we adopt the following two-way panel data model, considering the features of data in Japan[10]:

$$\begin{aligned} \ln\left(\mathrm{TFP}_{i,s,t}\right) &= \alpha_s + \gamma_s \ln\left(B_{i,t}\right) + u_{i,s,t}; \\ u_{i,s,t} &= \mu_{i,s} + \lambda_{s,t} + \nu_{i,s,t}; \end{aligned} \tag{18}$$

where γ_s is a parameter related to the infrastructure stock $B_{i,t}$, and expresses the relationship between infrastructure stock and TFP in industry s. In addition, $\mu_{i,s}$ expresses the specific effect of prefecture i in industry s; $\lambda_{s,t}$ expresses the unique effect of time t in industry s; and $\nu_{i,s,t}$ is a usual error term. Since the random effects model requires a rather strong assumption of no correlation between $\mu_{i,s}$ and the explanatory variables, we use the 2FE model. As described in Subsection 3.4, when the TFP or infrastructure stock series do not satisfy stationarity, the 2FE model suffers from spurious correlation, which may lead to erroneous policy implications. Thus, we conduct a unit root test using panel data. Then, we employ the panel ARDL model shown in Eq. (11), in addition to the 2FE model (the suffix for sector s is omitted for simplicity in Eq. (11)).

Fig. 2: "Toll roads" + "non-toll roads", around here

4.2.2 Results of cross-sectional dependence test

[10] Another option may include the use of interactive fixed effects model (Bai, 2009).

Methods for the panel unit root test can be divided into the first generation, where cross-sectional dependence (CD) across regions is not considered (Im et al., 2003; Levin et al., 2002; Baltagi, 2005), and the second generation, where it is considered (Pesaran, 2007). Hence, we first check for the existence of CD for the given series in the panel datasets. The null hypothesis is given as $H_0: \rho_{i,j} = Cov\left(v_{i,t}, v_{j,t}\right) = 0$ for $i \neq j$, where subscription s is omitted for simplicity. Based on the product–moment correlation coefficient

$$\hat{\rho}_{i,j} = \frac{\sum_{t=1}^{T} \hat{v}_{i,t}\hat{v}_{j,t}}{\left(\sum_{t=1}^{T} \hat{v}_{i,t}^2\right)^{\frac{1}{2}}\left(\sum_{t=1}^{T} \hat{v}_{j,t}^2\right)^{\frac{1}{2}}}; \tag{19}$$

with residuals of 2FE model, $\hat{v}_{i,t}$ and $\hat{v}_{j,t}$, several test statistics are defined as follows:

- Breusch-Pagan LM (Breusch and Pagan, 1980):

$$LM = \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T\hat{\rho}_{i,j}^2 \rightarrow \chi^2_{\frac{N(N-1)}{2}} \tag{20}$$

- Pesaran scaled LM (Pesaran, 2021):

$$LM_p = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(T\hat{\rho}_{i,j}^2 - 1\right) \rightarrow N(0,1) \tag{21}$$

- Bias-corrected scaled LM (Baltagi et al., 2012):

$$LM_{BC} = \sqrt{\frac{1}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \left(T\hat{\rho}_{i,j}^2 - 1\right) - \frac{N}{2(T-1)} \rightarrow N(0,1) \tag{22}$$

- Pesaran CD (Pesaran, 2021):

$$CD_p = \sqrt{\frac{2}{N(N-1)}} \sum_{i=1}^{N-1} \sum_{j=i+1}^{N} T\hat{\rho}_{i,j} \rightarrow N(0,1) \tag{23}$$

Table 2 (road capital stock) and Table 3 (TFP by Sector) show that the null hypothesis of no cross-sectional dependence for both road infrastructure and TFP by sector is rejected at the 1% significance level for all test types. Hence, we use the second-generation panel unit root test.

Table 2: Results of the cross-sectional dependence test (road capital stock), around here

Table 3: Results of the cross-sectional dependence test (TFP by sector), around here

4.2.3 Results of the panel unit root test

We use the second-generation panel unit root test of Pesaran (2007), termed as Cross-sectionally Augmented Im, Pesaran,- and Shin (CIPS) test. Consider the following augmented Dickey–Fuller (ADF) type regression.

$$\Delta y_{i,t} = \boldsymbol{z}'_{it}\boldsymbol{\gamma}_i + \rho_i y_{i.t-1} + \sum_{k=1}^{p} \Phi_{i,k} \Delta y_{i,t-k} + \nu_{i,t}; \tag{19}$$

where $y_{i,t}$ is a series of TFPs or road stock, $\boldsymbol{\gamma}_i, \rho_i$, and $\Phi_{i,k}$ are parameters. If we consider the constant term and trend, then $\boldsymbol{z}_{it} = (1, t)'$; hence, $\boldsymbol{z}'_{it}\boldsymbol{\gamma}_i$ represents panel-specific means and linear time trends. We assume that $\nu_{i,t}$ is independently and normally distributed for all values of i and t, allowing $\varepsilon_{i,t}$ to have heterogeneous variances σ_i^2 across panels. Here, the null hypothesis H_0: $\rho_i = 0$ for all values of i and the alternative hypothesis H_a: $\rho_i < 0$ for at least one unit i, that is, at least one of the series in the panel is generated by a stationary process. Pesaran (2007) extends this equation to the following cross-sectional augmented ADF (CADF) regression:

$$\Delta y_{i,t} = \boldsymbol{z}'_{it}\boldsymbol{\gamma}_i + \rho_i y_{i.t-1} + \sum_{k=1}^{p} \Phi_{i,k} \Delta y_{i,t-k} + \alpha_i \bar{y}_{t-1} + \sum_{k=1}^{p} \beta_{i,k} \Delta \bar{y}_{i,t-k} + \nu_{i,t}; \tag{20}$$

where $\bar{y}_t$ and $\Delta\bar{y}_{i,t-k}$ denote cross-sectional means of $y_{i,t}$ and $\Delta y_{i,t-k}$, respectively, and α_i and $\beta_{i,k}$ are parameters. Pesaran (2007) shows that adding $\bar{y}_{t-1}$ and $\Delta\bar{y}_{i,t-k}$ are sufficient for asymptotically filtering out the effects of the unobserved common factor. They base the test of the unit root hypothesis on the t-ratio of the OLS estimate of ρ_i, say τ_i^{CADF}. Then, as in Im et al. (2003), the panel unit root test is defined as a pooled version of the individual CADF statistics, called CIPS statistics.

$$\tau^{CIPS} = \sum_{i=1}^{N} \tau_i^{CADF};$$

where N is the sample size. The CIPS test does not have a standard limiting distribution; however, the critical values for popular scenarios are derived via simulation and tabulated in Pesaran (2007). Lag length p can be determined using an information criterion. In this study, we used the Bayesian Information criterion (BIC).

Tables 4 (road capital stock) and 5 (TFP by Sector) present the panel unit root test results at level and first-difference. For $\boldsymbol{z}_{it}$, we consider the cases of A) neither constant nor trend, B) with constant, and C) with constant and trend. Table 4 indicates that for cases A) and B), the null hypotheses are rejected at the 1% level, even though the road capital stock is at level; however, in case C), it can only be rejected when the first-order difference is taken, from which we conservatively conclude that road capital stock is in the I(1) series. For TFP, Table 5 indicates that at level, the null hypothesis could not be rejected even at the 10% level for many sectors. However, when the first difference is taken, the null hypothesis can be rejected for all sectors. These results suggest that the TFP series is either I(0) or I(1). Thus, owing to the combination of I(1) and I(0) variables, we adopt the panel ARDL model.

Table 4: Results of the panel unit root test (road capital stock), around here

Table 5: Results of the panel unit root test (TFP by sector), around here

4.2.4. Estimation results

As discussed in Subsection 4.2.3, the infrastructure capital stock and TFP of some sectors are suggested to be I(0) or I(1). If the series in the panel is generated by a nonstationary process, it can be stationarized by taking the difference between each variable. However, the cost of this approach is loss of information regarding long-term relationships. Table 6 presents the estimation results of the 2FE, FD, and panel ARDL (PMG estimation)[11] models. For the panel ARDL model in Eq. (12), the lag length of p and q is set based on BIC, with the assumption that the maximum possible length is four ($0 \leq p \leq 4$, $0 \leq q \leq 4$). We assume a constant term for the estimation. Standard errors are clustered at the prefecture level for 2FE and FD models.

For the 2FE model, we find that the effect of road infrastructure on TFP is negative in ten sectors (textiles; chemicals; non-metallic mineral products; transport equipment; other manufacturing; construction; electricity, gas and water supply; finance and insurance; real estate; and private non-profit services), while the effect is positive in nine other sectors (agriculture, forestry, and fishing; mining; food products and beverages; fabricated metal products; machinery; electrical machinery; wholesale and retail; transport and communications; and government services). However, in the case of the FD model, the effect is negative for only four sectors (construction, real estate, transport and communication; and government services). Although both the 2FE and FD models consider time-invariant unit-specific effects, we find relatively large differences in the estimated values at the sign level. The large difference in the coefficient estimates between the 2FE and FD models is a symptom of violation of the strict exogeneity assumption. In other words, if $v_{i,t}$ is correlated with $\ln(B_{i,t})$ for any t and s, the 2FE and FD models generally have different probability limits. If our model represents a spurious regression, then the 2FE model is no longer superior to the FD model[12] . This indicates the risk of blindly using the 2FE model in a series with non-stationarity. Nevertheless, we note that the FD model considers only short-term effects (Munnell, 1992).

Adding lagged $\ln(B_{i,t})$ can improve the endogeneity problem if it is correlated with $v_{i,t}$ (Wooldridge, 2010, p.322). Table 6 presents the PMG estimation results for the panel ARDL model. Fig.3 shows the PMG estimates for each sector ordered by magnitude. Table 6 verifies the existence of a significantly positive impact at the 1% level in nine sectors (non-metallic mineral products; machinery; electrical machinery; transport equipment; other manufacturing; wholesale and retail; finance and insurance; transport and communications; and government services) and a significantly negative effect in six sectors (agriculture, forestry, and fishing; food products and beverages; textiles; construction; real estate; and private non-profit services). Moreover, we find no significant impact in four sectors (mining; chemicals; fabricated metal products; and electricity, gas, and water supply). Fig. 3 shows that the strongest impacts in terms of elasticity are found in the transport equipment sector. It is followed by government services; transport and communications; non−metallic mineral products; and wholesale and retail. The estimates for these sectors are sizable, that is, they are above 0.2.

As road capital stock is rising almost consistently, we try to interpret the results in Table 6 based on the diagram of TFP transition by industry. We visually divide the TFP transition patterns by industry into three categories: *Rising*, *Constant*, and *Falling*.

[11] Shows estimation results only for the coefficients of long-term effects. Although the report of results is omitted, the error-correcting speed of adjustment term ϕ_i was negative for all sectors and significant at 1%.

[12] See Wooldridge (2010) for a detailed discussion.

(1) *Rising*: Chemicals; non-metallic mineral products; machinery; electrical machinery; transport equipment; wholesale and retail; finance and insurance; transport and communications; and government services.
(2) *Constant*: Agriculture, forestry, and fishing; textiles; mining; food products and beverages; fabricated metal products; other manufacturing; and electricity, gas, and water supply.
(3) *Falling*: Construction; real estate; and private non-profit services.

The results for sectors categorized as *Falling* may be difficult to interpret because falling TFP may mainly be caused by reasons other than infrastructure. For instance, in the construction sector, the reasons may include changes in public procurement policy and the difficulty of adjusting labor and capital costs to decrease value added. In the case of total, TFP has increased over time (Fig. 1). The coefficient estimate for the 2FE model is negative but insignificant[13]. However, the estimates for both the FD and ARDL models are positive. In the ARDL model, the elasticity of aggregate TFP to road stock is 0.05 ($p < 0.01$), in case of the ARDL model. The 2FE model result may suffer from spurious regression because of ignorance of non-stationarity.

For agriculture, forestry, and fishing, the TFP transition diagram (Fig. 1) shows a mix of prefectures with rising and falling TFP; however, the overall trend is downward. As road capital stock increases, the estimated coefficient naturally becomes negative. Table 4 suggests that, in the case of ARDL, which captures the long-term relationship, it is estimated to be negative, but in the case of DF, the estimate is positive. Meanwhile, for electrical machinery and wholesale and retail, the fluctuations in the transition diagram among prefectures are small and are consistently increasing, the estimates for 2FE, FD, and ARDL models are all positive. As shown in these illustrations, the estimates by the panel ARDL model are economically reasonable with respect to the movement of TFP (*Rising*, *Constant*, and *Falling*).

The analysis results show that road infrastructure has a positive impact on TFP in many industries from 1973 to 2012. Japan's rapid economic growth is generally considered to have occurred from 1954 to 1973, and the analysis period in this study is the period after the rapid economic growth. Under the principle of "balanced development of national land," since the early 1970s, Japan has made administrative investments with preferential treatment to rural areas over the three major metropolitan areas, and positive effects have been achieved even during this period, which may provide useful reference for national land planning in developed and developing countries.

Table 6: Results of the panel analysis, around here

Fig.3: PMG estimates for each sector ordered by its magnitude, around here

As Fig. 2 shows, road capital stock is likely to be larger in prefectures with large areas, such as Hokkaido. Therefore, we define the new variable of road capital stock per capita as road capital stock divided by the area of each prefecture to check the robustness of the estimation results. Table 7 shows that when the definitions of the infrastructure variables are changed, the signs of the estimated values are consistent, except for textiles, and no significant difference is found in the coefficient estimates. Therefore, we find that changing the definition of the variable does not have a substantial effect on interpretation.

[13] Martínez-Zarzoso and Bengochea-Morancho (2004) also find different results between static fixed effects model and PMG.

Table 8 shows the ARDL model estimation results for the first 20 years (1972-1992) and last 20 years (1992-2012)[14]. Road investment has increased significantly in the 1990s due to economic stimulus measures but has declined in the 2000s. However, the impact of increased investment may last for a few years in the ARDL specification, owing to the introduction of lag terms (Beck and Katz, 2011). Total TFP shows a consistent upward trend, with a significant increase around 2010. TFP trends in the finance and insurance and textile industries have changed from negative to positive after 1990. The ARDL model estimates successfully captured these TFP trends. Overall, the elasticity of aggregate TFP to road stock during the first 20 years is 0.09 ($p < 0.01$) and 0.18 ($p < 0.01$) for the last 20 years. These results indicate that road infrastructure has a positive impact on TFP, and this impact exists even in the 1992-2012 period.

Table 7: Robustness check, around here

Table 8: Results of the panel analysis by time period, around here

5. Conclusions

This study analyzes the relationship between road infrastructure capital stock and TFP using the R-JIP 2017 database of productivity by industry and prefecture in Japan. We estimate TFP based on Hulten et al.'s (2006) growth accounting framework and derive estimates without specifying the functional form of a production function. We perform a long-term analysis by industry for each prefecture in Japan for the 1972–2012 period, which corresponds to the period following Japan's rapid economic growth. In addition, the possibility of unit roots is explicitly considered in the panel data for road infrastructure stock and TFP to eliminate spurious correlations. The results of the second-generation panel unit root test indicate that the road infrastructure variable is conservatively concluded to be I(1), and that of TFP is either I(1) or I(0), depending on the sector. Therefore, a panel ARDL model is used, in which a mixture of I(0) and I(1) variables is allowed, and the PMG method is used for estimation (Pesaran et al.,1999).

The panel ARDL model estimation results show that the elasticity of aggregate TFP to road stock is 0.05 ($p < 0.01$) and has a positive effect on 11 out of 18 industries. In particular, the effect of infrastructure tends to be positive during periods of increased value-added and TFP. The strongest impact is found for transport equipment, followed by government services and transport and communications. The panel ARDL model results significantly differ from those of the 2FE model, which tends to underestimate (negatively) the effect of road infrastructure as a whole. The blind use of the 2FE model is customary in current empirical research. Future studies should validate the results of this study using different methods, such as VAR (Annala et al., 2008) and the same dataset, R-JIP 2017. Additionally, future research can include data before the period of high economic growth in a manner consistent with the R-JIP database. Moreover, the results in spatial units can be examined in the context of Japan, as argued by Munnell (1992).

[14] The estimate does not converge for the service sector (private, non-profit) from 1972 to 1992.

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Tables

Table 1: List of industries with negative real value added

Year	Prefecture	Sector	Real value added (price in 2000; million)
1974	Ehime	Petroleum and coal products	–33446.54
1982	Mie	Petroleum and coal products	–17413.19
2011	Tottori	Pulp, paper and paper products	–1726.92
1986	Yamaguchi	Petroleum and coal products	–381841.57
2008	Ehime	Petroleum and coal products	–11350.18
2009	Ehime	Basic metal	–6111.88
1972	Kochi	Precision instruments	–59.28
2008	Kochi	Precision instruments	–3815.36
2009	Kochi	Precision instruments	–3354.57
2010	Kochi	Precision instruments	–8706.00
2011	Kochi	Precision instruments	–13354.76
2012	Kochi	Precision instruments	–7061.16
1972	Oita	Basic metal	–1364.17
1988	Okinawa	Petroleum and coal products	–17601.48
1972	Okinawa	Precision instruments	–73.58

Table 2: Results of the cross-sectional dependence tests (road capital stock)

Test type	Value
Breusch-Pagan LM	41711.94544
Pesaran scaled LM	894.0527847
Bias-corrected scaled LM	893.4777847
Pesaran CD	204.2279777

$p < 0.01$ for all results. Results are obtained using Eviews13.

Table 3: Results of the cross-sectional dependence test (TFP by sector)

Sector	Test type			
	Breusch-Pagan LM	Pesaran scaled LM	Bias-corrected scaled LM	Pesaran CD
Total	26518.12297	560.1024562	559.5274562	151.0619082
Agriculture, forestry and fishing	11617.01902	232.5858904	232.0108904	47.6764025
Mining	10026.92436	197.6366447	197.0616447	81.92929669
Food products and beverages	14994.38143	306.8181178	306.2431178	94.59781034
Textiles	22258.05449	466.4689239	465.8939239	142.5001206
Chemicals	30689.52738	651.78721	651.21221	173.1354534
Non-metallic mineral products	22900.88085	480.5978288	480.0228288	143.899402
Fabricated metal products	22933.87966	481.3231213	480.7481213	146.7185358
Machinery	25161.86761	530.2928463	529.7178463	154.9339248
Electrical machinery	40475.00981	866.8657447	866.2907447	201.1484854
Transport equipment	24032.22309	505.463995	504.888995	150.6395808
Other manufacturing	16690.17314	344.0905159	343.5155159	119.2040984
Construction	18274.97301	378.9233854	378.3483854	117.5779991
Electricity, gas and water supply	11399.60328	227.8072338	227.2322338	90.30819481
Wholesale and retail	37444.79349	800.2635624	799.6885624	193.3428519
Finance and insurance	35936.86701	767.1203197	766.5453197	189.1764219
Real estate	39937.60954	855.0540364	854.4790364	199.7686844
Transport and communications	19374.74114	403.0955732	402.5205732	112.590692
Private non-profit services	36277.46101	774.6063541	774.0313541	189.260353
Government services	31981.00712	680.1730942	679.5980942	173.8696953

$p < 0.01$ for all results. Results are obtained using Eviews13.

Table 4: Results of the panel unit root test (road capital stock)

	Level		First-difference	
Control variables	CIPS	p-values	CIPS	p-values
None	-2.509	<0.01	-2.136	<0.01
Constant	-2.056	<0.10	-2.411	<0.01
Constant and Trend	-2.358	>=0.10	-2.583	<0.10

Table 5: Results of the panel unit root test (TFP by sector)

Sector	Control variables	Level CIPS	Level p-values	First-difference CIPS	First-difference p-values
Total	None	-0.932	>=0.10	-4.760	<0.01
	Constant	-2.235	<0.05	-4.972	<0.01
	Constant and Trend	-2.411	>=0.10	-4.796	<0.01
Agriculture, forestry and fishing	None	-0.895	>=0.10	-5.618	<0.01
	Constant	-2.078	<0.10	-5.656	<0.01
	Constant and Trend	-2.067	>=0.10	-5.836	<0.01
Mining	None	-1.698	<0.05	-4.593	<0.01
	Constant	-1.904	>=0.10	-4.478	<0.01
	Constant and Trend	-2.222	>=0.10	-4.432	<0.01
Food products and beverages	None	-1.043	>=0.10	-6.115	<0.01
	Constant	-2.085	<0.10	-5.740	<0.01
	Constant and Trend	-2.434	>=0.10	-5.244	<0.01
Textiles	None	-1.811	<0.01	-7.061	<0.01
	Constant	-1.899	>=0.10	-7.199	<0.01
	Constant and Trend	-3.084	<0.01	-6.904	<0.01
Chemicals	None	-1.643	<0.05	-1.643	<0.05
	Constant	-1.965	>=0.10	-5.278	<0.01
	Constant and Trend	-2.929	<0.01	-5.487	<0.01
Non-metallic mineral products	None	-1.519	<0.10	-6.227	<0.01
	Constant	-2.249	<0.01	-5.999	<0.01
	Constant and Trend	-2.463	>=0.10	-5.607	<0.01
Fabricated metal products	None	-2.320	<0.01	-6.557	<0.01
	Constant	-2.598	<0.01	-6.391	<0.01
	Constant and Trend	-2.207	>=0.10	-5.851	<0.01
Machinery	None	-2.475	<0.01	-6.206	<0.01
	Constant	-2.906	<0.01	-6.211	<0.01
	Constant and Trend	-3.395	<0.01	-6.241	<0.01
Electrical machinery	None	-1.925	<0.01	-6.474	<0.01
	Constant	-2.605	<0.01	-6.143	<0.01
	Constant and Trend	-2.845	<0.01	-6.190	<0.01

Table 5: Results of the panel unit root test (TFP by sector) cont.

Sector	Control variables	Level CIPS	Level p-values	First-difference CIPS	First-difference p-values
Transport equipment	None	-2.504	<0.01	-5.823	<0.01
	Constant	-3.122	<0.01	-5.964	<0.01
	Constant and Trend	-3.526	<0.01	-5.702	<0.01
Other manufacturing	None	-1.723	<0.01	-6.219	<0.01
	Constant	-2.283	<0.01	-6.088	<0.01
	Constant and Trend	-3.201	<0.01	-6.018	<0.01
Construction	None	-2.068	<0.01	-5.622	<0.01
	Constant	-2.437	<0.01	-5.499	<0.01
	Constant and Trend	-2.437	<0.01	-5.324	<0.01
Electricity, gas and water supply	None	-1.552	<0.05	-4.359	<0.01
	Constant	-2.319	<0.01	-4.557	<0.01
	Constant and Trend	-2.931	<0.01	-4.604	<0.01
Wholesale and retail	None	-2.196	<0.01	-5.736	<0.01
	Constant	-2.965	<0.01	-5.840	<0.01
	Constant and Trend	-3.126	<0.01	-5.300	<0.01
Finance and insurance	None	-2.175	<0.01	-5.627	<0.01
	Constant	-2.631	<0.01	-5.675	<0.01
	Constant and Trend	-2.891	<0.01	-5.517	<0.01
Real estate	None	-1.859	<0.01	-3.795	<0.01
	Constant	-3.707	<0.01	-3.758	<0.01
	Constant and Trend	-3.654	<0.01	-3.794	<0.01
Transport and communications	None	-1.642	<0.05	-5.453	<0.01
	Constant	-2.768	<0.01	-5.421	<0.01
	Constant and Trend	-2.740	<0.01	-5.245	<0.01
Private non-profit services	None	-1.475	<0.10	-4.829	<0.01
	Constant	-2.942	<0.01	-5.099	<0.01
	Constant and Trend	-3.380	<0.01	-5.017	<0.01
Government services	None	-1.434	>=0.10	-5.795	<0.01
	Constant	-2.732	<0.01	-5.646	<0.01
	Constant and Trend	-3.215	<0.01	-5.574	<0.01

Table 6: Results of the panel analysis

	2FE				FD				ARDL			
Sector	Coef.	Std.Err.	t	P>|t|	Coef.	Std.Err.	t	P>|t|	Coef.	Std.Err.	t	P>|t|
Total	-0.018436	0.0482821	-0.38	0.704	0.0281484	0.0173797	1.62	0.112	0.0504806	0.0065978	7.65	0.000
Agriculture, forestry and fishing	0.240804	0.1088465	2.21	0.032	0.1036924	0.0366981	2.83	0.007	-0.053414	0.0111371	-4.80	0.000
Mining	0.0417344	0.2032584	0.21	0.838	0.2445381	0.093035	2.63	0.012	-0.071253	0.0285752	-2.49	0.013
Food products and beverages	0.0840584	0.0985508	0.85	0.398	0.5210099	0.0545367	9.55	0.000	-0.246356	0.0172861	-14.25	0.000
Textiles	-0.039877	0.1203393	-0.33	0.742	0.4443323	0.038956	11.41	0.000	-0.110327	0.0292633	-3.77	0.000
Chemicals	-0.091111	0.2429087	-0.38	0.709	0.6308107	0.0917778	6.87	0.000	0.1293317	0.1050484	1.23	0.218
Non-metallic mineral products	-0.098612	0.1100839	-0.90	0.375	0.1627642	0.0441706	3.68	0.001	0.2649028	0.0136152	19.46	0.000
Fabricated metal products	0.266287	0.096349	2.76	0.008	0.6127204	0.0493216	12.42	0.000	0.0027885	0.0205056	0.14	0.892
Machinery	0.1228523	0.1398826	0.88	0.384	0.320073	0.0496629	6.44	0.000	0.1942475	0.0233008	8.34	0.000
Electrical machinery	0.2678546	0.2165316	1.24	0.222	0.3770476	0.0753984	5.00	0.000	1.3188231	0.1115942	11.82	0.000
Transport equipment	-0.02693	0.1431961	-0.19	0.852	0.5368039	0.0968795	5.54	0.000	0.2942298	0.0322331	9.13	0.000
Other manufacturing	-0.063693	0.065056	-0.98	0.333	0.0465849	0.0269864	1.73	0.091	0.1076674	0.0115046	9.36	0.000
Construction	-0.18391	0.1065622	-1.73	0.091	-0.059061	0.0457793	-1.29	0.204	-0.122973	0.0119344	-10.30	0.000
Electricity, gas and water supply	-0.04459	0.142354	-0.31	0.756	0.3058782	0.0543688	5.63	0.000	0.0245729	0.0162911	1.51	0.132
Wholesale and retail	0.0342581	0.09581	0.36	0.722	0.3015516	0.0305857	9.86	0.000	0.2533845	0.0302544	8.38	0.000
Finance and insurance	-0.079609	0.0809417	-0.98	0.331	0.3480279	0.0357576	9.73	0.000	0.1986782	0.0353015	5.63	0.000
Real estate	-0.153475	0.1513128	-1.01	0.316	-0.640187	0.0517552	-12.37	0.000	-0.229718	0.0662166	-3.47	0.001
Transport and communications	0.0279533	0.1046445	0.27	0.791	-0.065464	0.0300787	-2.18	0.035	0.2788523	0.0195862	14.24	0.000
Private non-profit services	-0.104239	0.0745699	-1.40	0.169	0.0109708	0.0252341	0.43	0.666	-0.316618	0.0140215	-22.58	0.000
Government services	0.0482883	0.032981	1.46	0.150	-0.133397	0.0145295	-9.18	0.000	0.2910447	0.0693445	4.20	0.000

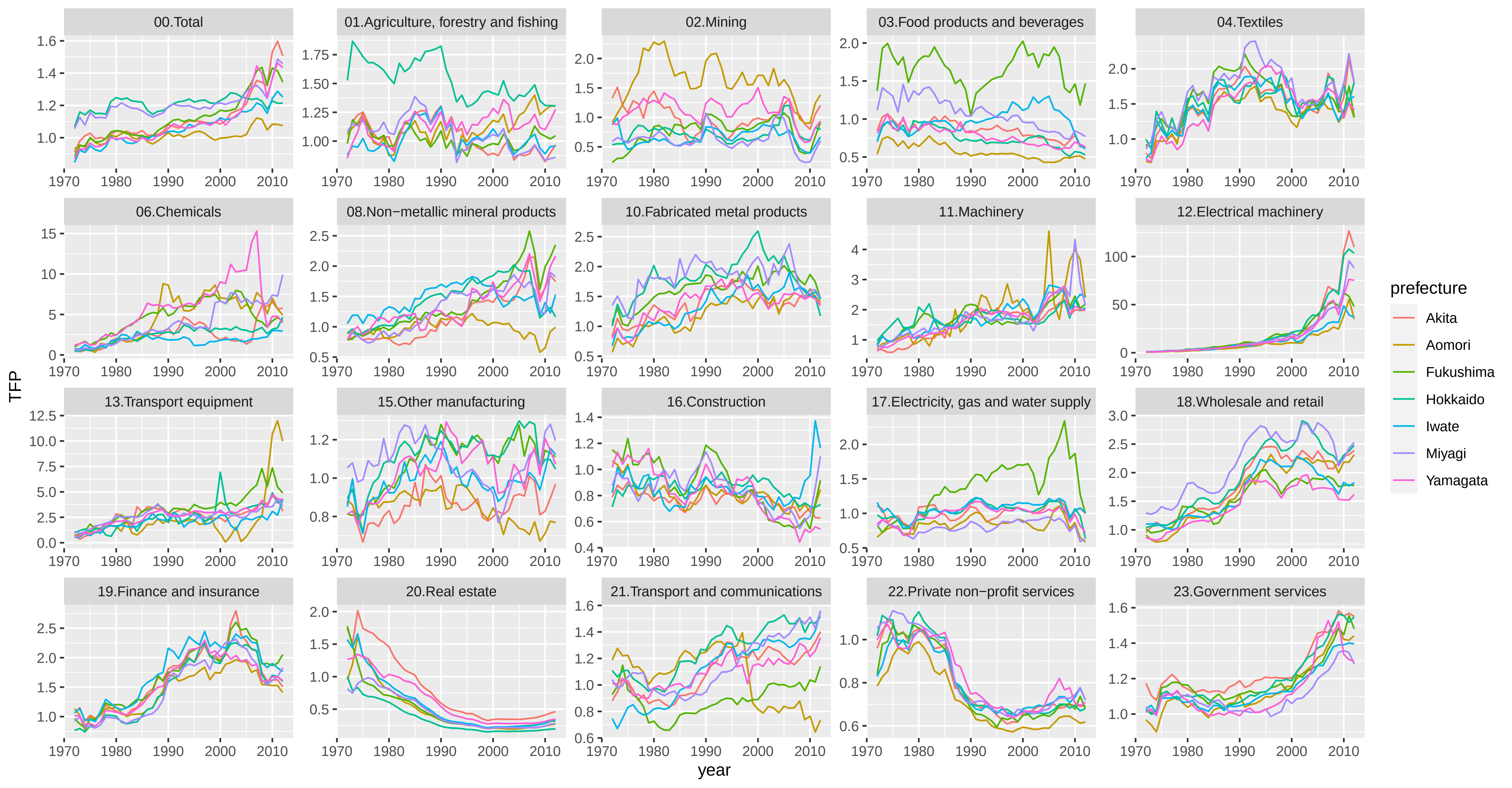
Standard errors are clustered at the prefecture level for 2FE and FD.

Table 7: Robustness check

Sector	ARDL			
	Road stock		Road stock per capita	
	Coef.	Std.Err.	Coef.	Std.Err.
Total	0.050	0.007	0.050	0.005
Agriculture, forestry and fishing	-0.053	0.011	-0.087	0.009
Mining	-0.071	0.029	-0.040	0.023
Food products and beverages	-0.246	0.017	-0.212	0.014
Textiles	-0.110	0.029	0.057	0.019
Chemicals	0.129	0.105	0.195	0.081
Non-metallic mineral products	0.265	0.014	0.232	0.017
Fabricated metal products	0.003	0.021	0.066	0.014
Machinery	0.194	0.023	0.228	0.019
Electrical machinery	1.319	0.112	1.233	0.150
Transport equipment	0.294	0.032	0.412	0.026
Other manufacturing	0.108	0.012	0.093	0.009
Construction	-0.123	0.012	-0.118	0.011
Electricity, gas and water supply	0.025	0.016	0.016	0.013
Wholesale and retail	0.253	0.030	0.215	0.029
Finance and insurance	0.199	0.035	0.179	0.034
Real estate	-0.230	0.066	-0.052	0.073
Transport and communications	0.279	0.020	0.229	0.016
Private non-profit services	-0.317	0.014	-0.301	0.014
Government services	0.291	0.069	0.362	0.112

Table 8: Results of the panel analysis, by time period

Sector	ARDL (1972-1992)				ARDL (1992-2012)			
	Coef.	Std.Err.	t	P>|t|	Coef.	Std.Err.	t	P>|t|
Total	0.091	0.006	14.250	0.000	0.176	0.010	16.890	0.000
Agriculture, forestry and fishing	-0.041	0.012	-3.366	0.001	0.062	0.017	3.719	0.000
Mining	0.249	0.030	8.422	0.000	0.046	0.049	0.935	0.350
Food products and beverages	-0.110	0.015	-7.253	0.000	0.116	0.034	3.404	0.001
Textiles	0.310	0.018	17.578	0.000	-0.242	0.048	-5.059	0.000
Chemicals	1.245	0.042	29.827	0.000	0.082	0.062	1.317	0.188
Non-metallic mineral products	0.262	0.015	17.316	0.000	0.291	0.015	19.705	0.000
Fabricated metal products	0.250	0.016	16.117	0.000	0.128	0.023	5.498	0.000
Machinery	0.342	0.029	11.759	0.000	0.311	0.044	7.071	0.000
Electrical machinery	1.354	0.052	26.263	0.000	4.152	0.392	10.589	0.000
Transport equipment	0.566	0.034	16.467	0.000	0.384	0.031	12.339	0.000
Other manufacturing	0.277	0.010	28.427	0.000	0.008	0.013	0.630	0.529
Construction	0.002	0.010	0.214	0.831	-0.047	0.019	-2.480	0.013
Electricity, gas and water supply	0.228	0.019	12.025	0.000	-0.127	0.027	-4.752	0.000
Wholesale and retail	0.759	0.086	8.802	0.000	0.115	0.015	7.529	0.000
Finance and insurance	0.734	0.063	11.656	0.000	-0.470	0.076	-6.213	0.000
Real estate	-1.159	0.069	-16.728	0.000	2.021	2.116	0.955	0.340
Transport and communications	0.115	0.021	5.552	0.000	0.141	0.019	7.379	0.000
Private non-profit services	Did not converge.				0.055	0.013	4.345	0.000
Government services	-0.048	0.007	-6.541	0.000	0.633	0.109	5.816	0.000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03.Food products and beverages
04.Textiles
06.Chemicals
08.Non−metallic mineral products
10.Fabricated metal products
11.Machinery
12.Electrical machinery
13.Transport equipment
15.Other manufacturing
16.Construction
17.Electricity, gas and water supply
18.Wholesale and retail
19.Finance and insurance
20.Real estate
21.Transport and communications
22.Private non−profit services
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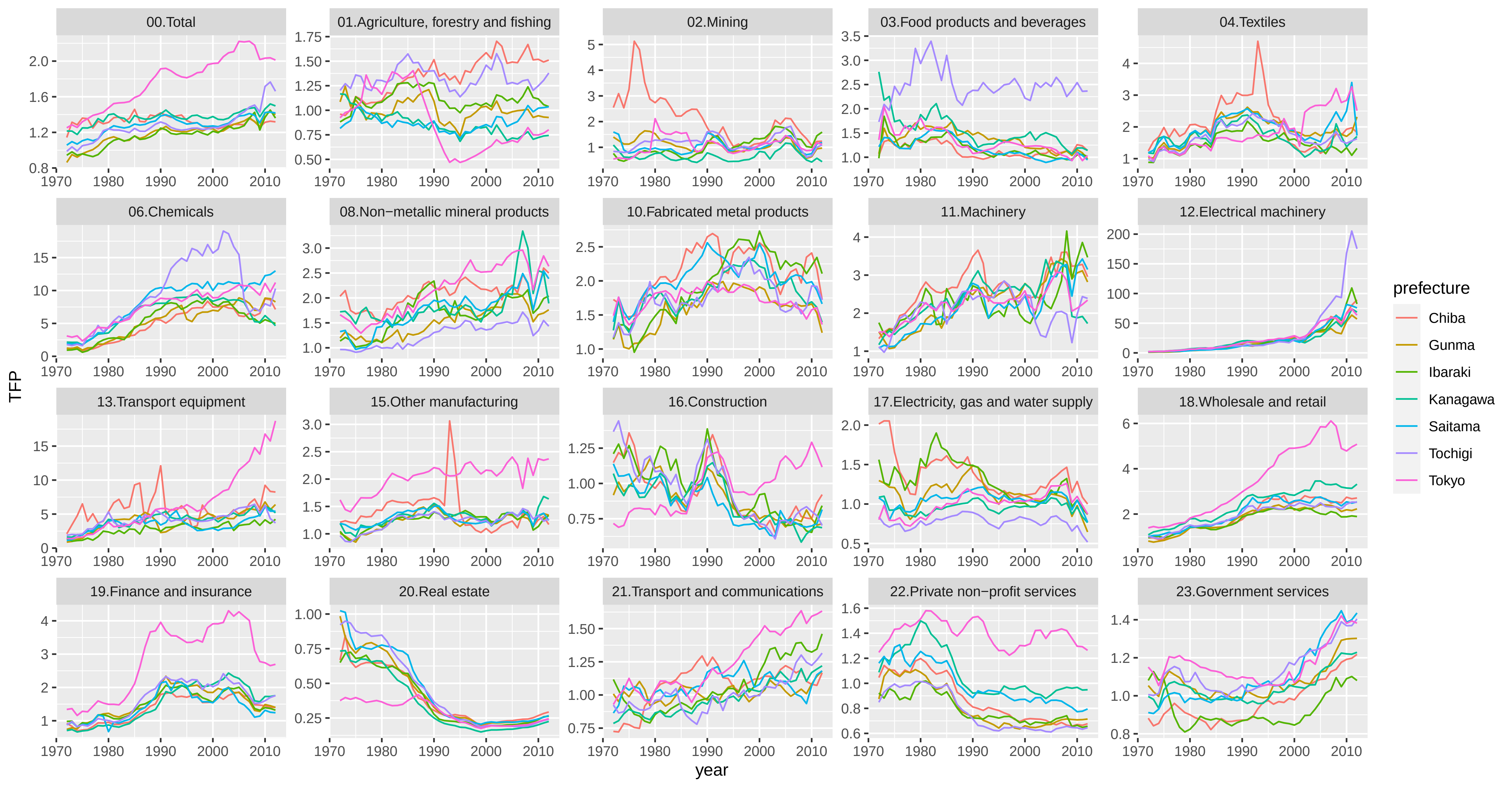
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20.Real estate
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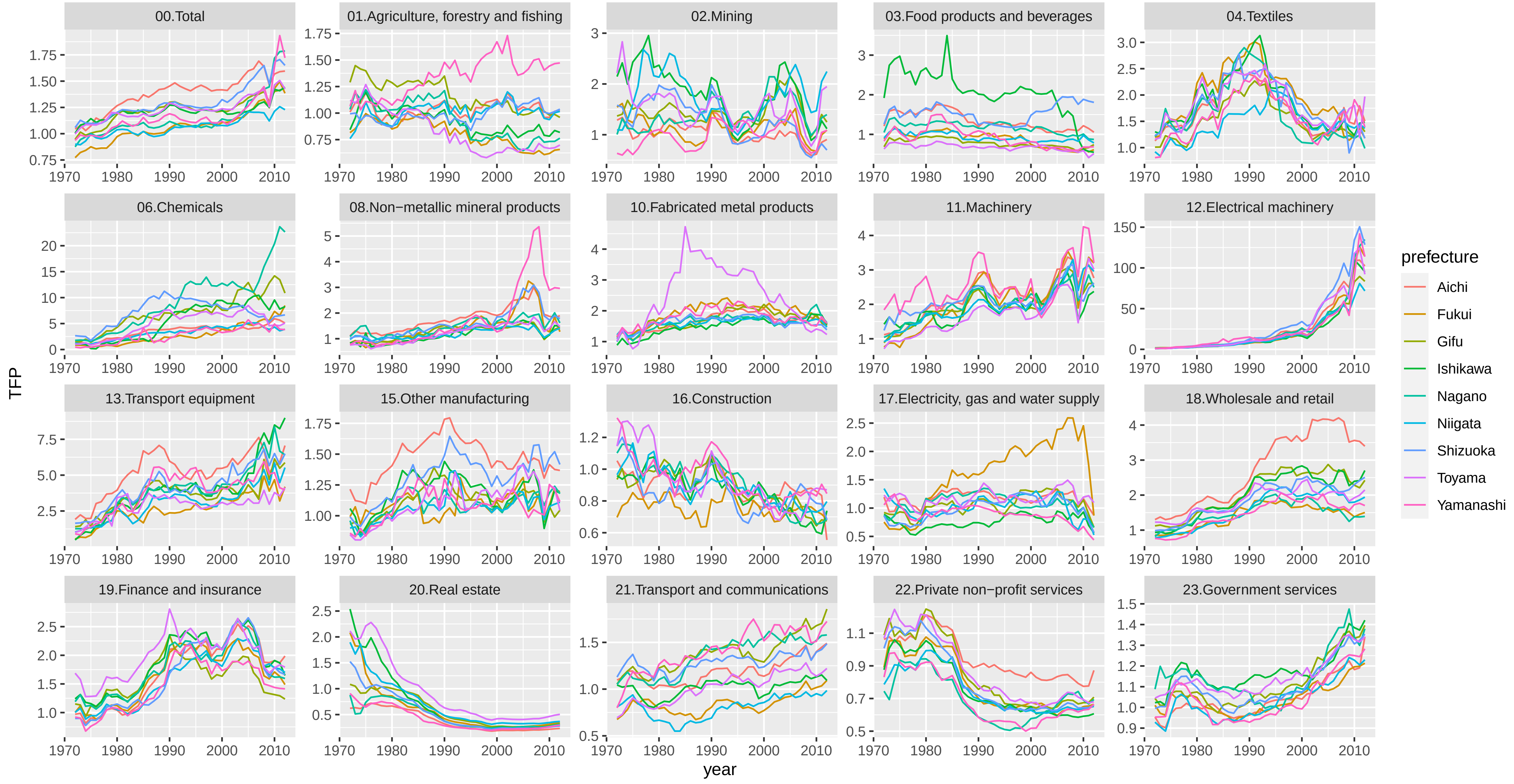

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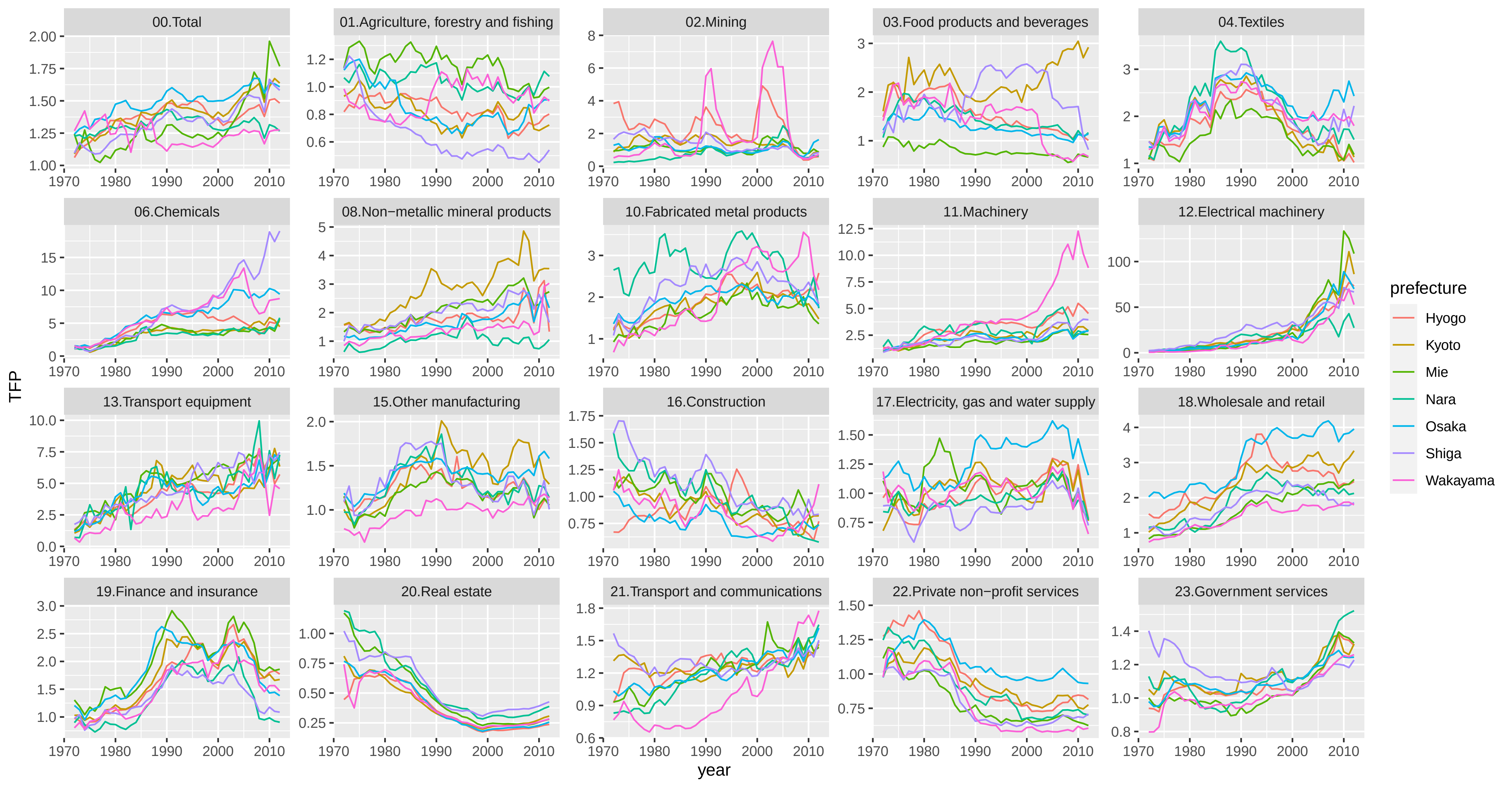
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13.Transport equipment
15.Other manufacturing
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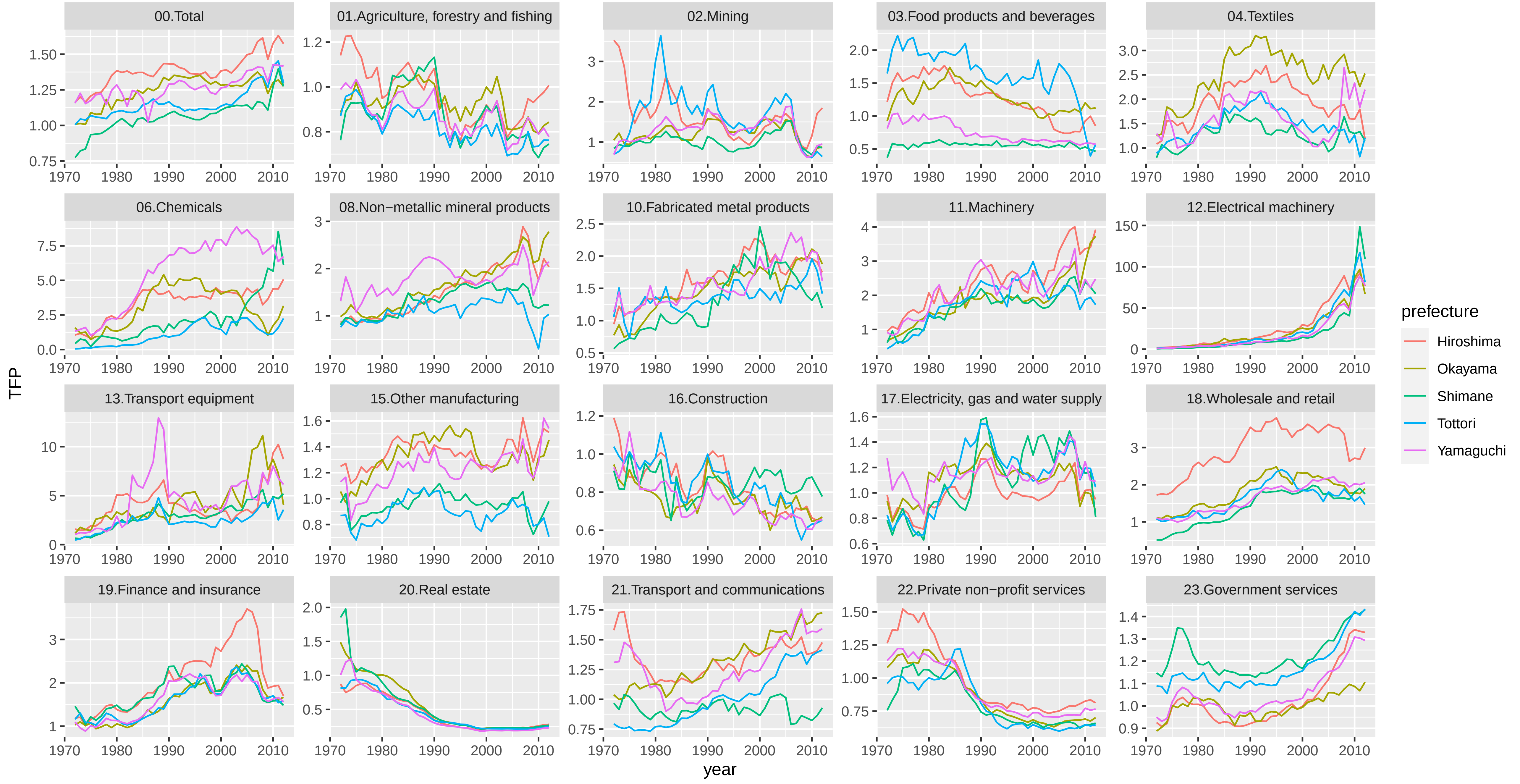
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20.Real estate
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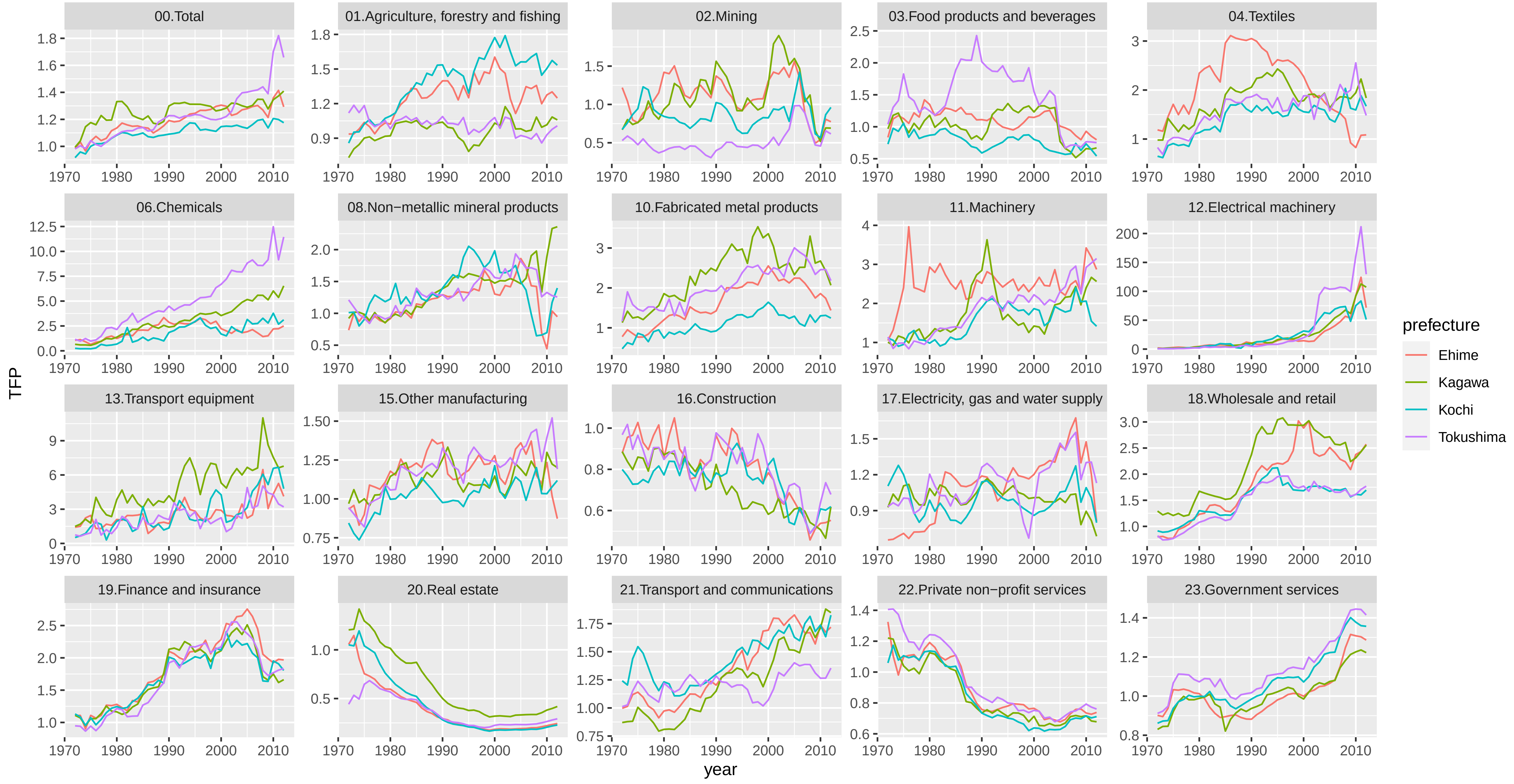
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04.Textiles
06.Chemicals
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11.Machinery
12.Electrical machinery
13.Transport equipment
15.Other manufacturing
16.Construction
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18.Wholesale and retail
19.Finance and insurance
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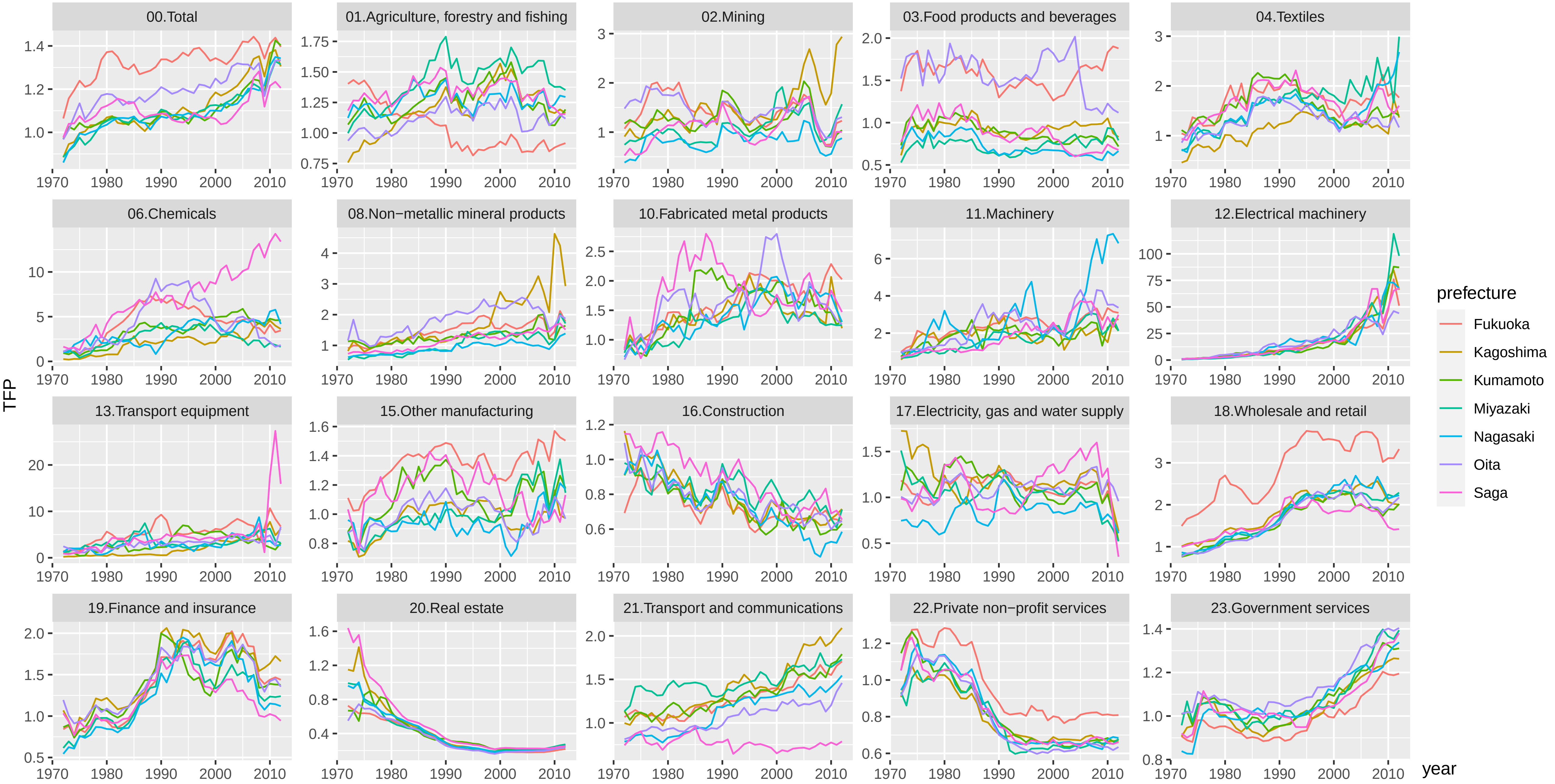

Figure 1 Changes in TFP index

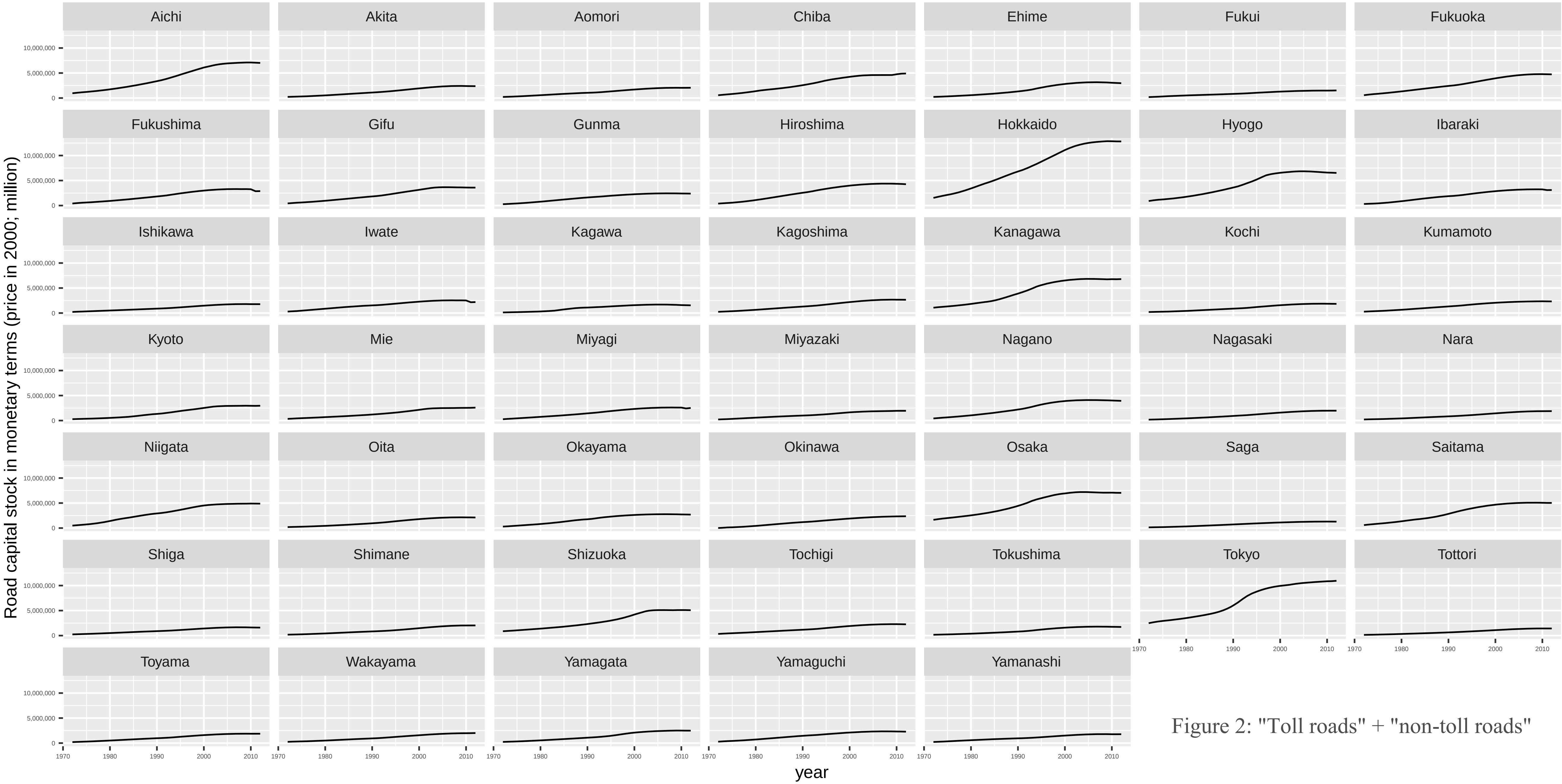

Figure 2: "Toll roads" + "non-toll roads"

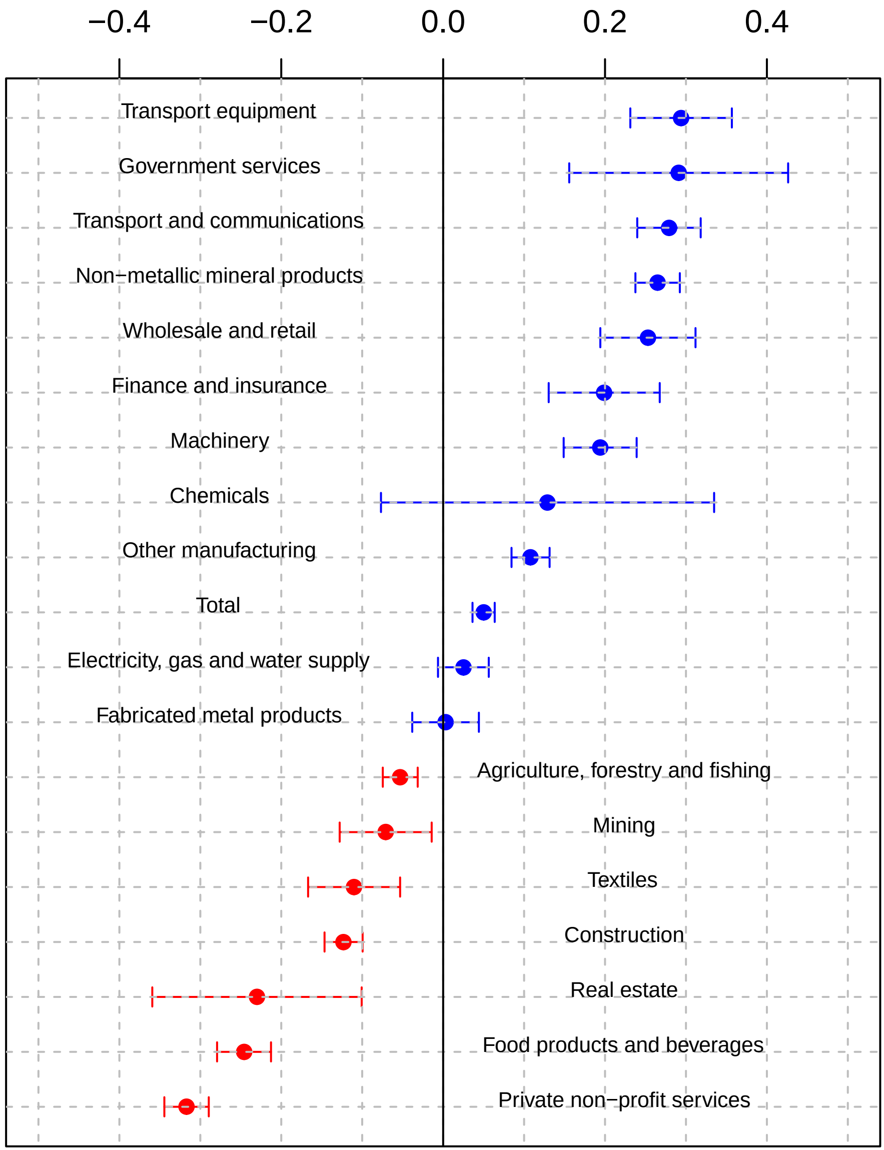

Figure 3: PMG estimates for each sector ordered by its magnitude