Aggregate Implications of Changing Industrial Trends in Japan*

Toyoichiro Shirota[†] and Satoshi Tsuchida[‡]

April 2024

Abstract

This study examines the extent to which the long-term declining trend in Japan's GDP growth rate is attributable to factors common to all the industries or those specific to individual industries. By applying Japan's 1958-2019 data to a multi-industry network model, we obtained the following results. First, common factors explain approximately 60% of the variation in Japan's long-term GDP growth rate. This result contrasts to that in the US: common factors explain only around 20% of the secular trend in US GDP growth. Second, however, the impact of industry-specific factors is non-negligible. In particular, machinery-industry-specific factors explain much of the low growth in the past 20 years. Finally, the spillover effects from individual industries to the aggregate GDP depend on the role of each industry in the production network, and in Japan, the influence of investment-related industries such as the machinery industries and construction is substantial.

JEL Classification: C32, E23, O41

Keywords: trend growth, industrial linkages, production network, growth accounting

*We would like to thank Shin-ichi Fukuda (the Editor-in-Chief), Junko Koeda (the Co-Editor), and anonymous referees. We also thank Kosuke Aoki, Ichiro Fukunaga, Yoshihiko Hogen, Ryo Jinnai, Takashi Nagahata, Jouchi Nakajima, Yoichi Ueno for comments and discussions. Shirota is grateful for financial support from JSPS KAKENHI Grant-in-Aid for Scientific Research(C) No. 21K01396. Any remaining errors are the authors' own. The views expressed in this paper are those of the authors and do not necessarily reflect those of the authors' affiliations.

[†]Aoyama Gakuin University, e-mail: t25733@aoyamagakuin.jp

[‡]Bank of Japan, e-mail: satoshi.tsuchida@boj.or.jp

1 Introduction

The topic of this paper is the long-term, gradual decline of Japan's economic growth rate. The country enjoyed the high-growth period from the 1950s to the early 1970s, entered a period of stable growth and a "bubble economy" in the 1980s, and subsequently faced a prolonged low-growth phase, often referred to as the "lost decades." Comprehending this long-term growth trend and its underlying drivers is pivotal for shaping effective growth strategies. Moreover, the trend growth rate exerts a significant influence on the natural rate of interest, which serves as a guideline for monetary policy operations. A particularly challenging aspect arises when the natural rate of interest is low, leading to difficulties due to the zero lower bound of interest rates.

This study aims to ascertain which of the factors—macroeconomic or industry-specific—predominantly influences the long-term aggregated trend growth rate. Macroeconomic factors common to all industries may play a significant role in determining the trend growth rate. Improvements in general purpose technology are the primary source of industry-common factors. Furthermore, structural issues like Japan's rigid labor markets and financial system have also served as common factors across various industries. Conversely, industry-specific factors may play a significant role in shaping the trend growth rate. The rise and fall of individual industries has potential to impact the aggregate trend growth rate. Identifying the more influential factor is crucial for developing growth policies and anticipating future shifts in the natural rate of interest. Thus, this research question holds significant policy relevance. Despite its importance, empirical research in the field of Japan's economic growth, particularly in this context, remains sparse. Our study begins by decomposing industrial trends in Total Factor Productivity (TFP) and labor into industry-common and industry-specific factors. It then investigates the extent to which the declining trend GDP growth rate can be attributed to these common and industry-specific factors.

Examining the causal effects of common and industry-specific factors on aggregate GDP growth rates poses significant challenges. The complexity arises because many industries are connected through the supply chain. As a result, a TFP improvement in one specific industry can trigger co-movements across many industries. To distinguish between these co-movements and those caused by the common factor, it is necessary to separately identify the impacts of common and industry-specific factors on GDP. In the current study, following Foerster et al. (2022), we employ a multi-industry economic model to overcome this identification issues.

The empirical analysis yields the following key findings. First, approximately 60% of the variation in Japan's low-frequency GDP growth is attributable to common factors. This contrasts with a previous study in US, which attributed around 20% of US low-frequency GDP growth variation to common factors. Second, the industry-specific factors are non-negligible. For example, over the past two decades when the natural rate is low and conventional monetary policy is constrained by the zero lower bounds, the primary cause of the low trend GDP growth was the decline in the machinery-industry-specific factors. Third, the spillover effects from individual industries to the aggregate GDP is contingent upon their role in the production and investment networks. In Japan, the influence of investment-related industries, such as machinery industries and construction, is substantial.

This study is a part of the literature on the Japan's long-term economic growth from the industry perspective. Similar to ours, Jorgenson and Motohashi (2005), Nakakuki et al. (2004), Kawamoto (2005), Fukao et al. (2007), Hayashi, ed (2007), Fukao and Miyagawa, eds (2008), Fueki and Kawamoto (2009), Kim et al. (2010), Fukao (2012), Jorgenson et al. (2015), Fukao et al. (2021a), Fukao, ed (2021), Fukao (2023) approach the Japan's long-run economic growth using industry data. These studies utilize the growth accounting approach to decompose GDP growth into contributions from various factor inputs, offering the advantage of minimal reliance on specific models. However, this approach falls short of distinguishing between common factors and those specific to individual industries that drive aggregate economic growth. Our study enhances this analytical framework by dissecting long-term GDP fluctuations into common and industry-specific elements, employing a model that incorporates inter-industry linkages. In doing so, our research serves as a valuable complement to these prior studies, providing a more nuanced understanding of the forces shaping economic growth.

This study is also related to the empirical literature on investment specific technological progress (ISTP) in Japan. This strand of literature includes Braun and Shioji (2007), Rodríguez-López and Torres (2012), Hirose and Kurozumi (2012), Kumano et al. (2014), Fueki et al. (2016), Hirakata and Koike (2018), and Takahashi and Takayama (2022a). Some of these studies focus on the role of ISTP in the business cycle frequencies. In contrast, our work concentrates on the role of the industry-specific technological progress in the low-frequency movements in the GDP growth rate.[1] Among the studies focusing on long-term growth, Braun and Shioji (2007) is noteworthy. Employing a two-sector model, they reveal that the ISTP, which is identified using the relative price of investments, helps to sustain the potential growth rate in the 1990s. Our study differs by analyzing multiple industries connected with networks, extending the period up to the 2010s, and not relying on the relative price of investments.[2]

There is a considerable number of research efforts through the lens of firm-level data. These studies include Nishimura et al. (2005), Matsuura and Motohashi (2005), Ahearne and Shinada (2005), Fukao and Kwon (2006), Ito and Lechevalier (2009), Kawakami and Miyagawa (2010), Kneller et al. (2012), Hogen et al. (2017), Ikeuchi et al. (2018), Nakamura et al. (2019), Fukao et al. (2021b), Hosono and Takizawa (2022), Miyakawa et al. (2022), Yagi et al. (2022), and Katagiri (2024). These research that utilize firm-level data aim to uncover the importance of business dynamics. Among others, studies like Fukao et al. (2006), Griffin and Odaki (2009), and Inui et al. (2015) conduct analyses covering relatively long periods. Many of these studies point out that the primary source of economic dynamics lies in productivity improvements within firms,

[1] Greenwood et al. (1997) stress the significance of ISTP for the long-run US economic growth.

[2] Several studies including Moura (2018) and Watanabe (2020) cast doubt on the reliability of the relative price of investment as a measure of ISTP.

and the effects of entry and exits are relatively small. This study, which employs industry-level data, benefits from incorporating amplification effects resulting from inter-industry transactions embedded in input-output tables.[3] Leveraging these characteristics, our objective is to clarify the driving forces behind the long-run economic growth.

In terms of the methodology, this study employs both a Bayesian statistical model and a multi-industry growth model, employing the analytical framework developed by Foerster et al. (2022). This study applies these models to Japan's data, discovering the contrasting outcomes when compared to those in the US: in Japan, the common factor accounts for 2/3 of variations in trend growth rate, whereas, in US, the industry-specific factors account for 4/5 of these variations. These results indicate that the major source of trend growth rate can vary significantly between countries.

The rest of the paper is organized as follows. Section 2 presents the long-term trend of GDP growth rate in Japan. Section 3 employs a statistical model and empirically describes the developments of TFP and labor growth rates in 1958-2019. Section 4 introduces a multi-industry general equilibrium model and quantifies the aggregate implications of common and industry-specific factors. Section 5 concludes the study.

2 The long-run movements of the GDP growth rate in Japan

To begin with, let us present the long-term trend of GDP growth rate in Japan. Unless otherwise noted, this paper employs the GDP growth rate per working-age population for the analyses.[4] Figure 1 depicts the GDP growth rates per working-age population over 1958-2019. The aggregate GDP growth rates are the weighted averages of 24 industries' value-added growth rates.[5] From this figure, we draw several implications.

First, the shifts in industry share have little effect on the aggregated GDP growth rate. In Figure 1, the black and green lines represent GDP growth rates aggregated with different weighting approaches: the black line uses fixed industry shares calculated as the average over the entire sample period (1958-2019), while the green line employs time-varying industry shares. The time variation of aggregation weights does not matter for the developments of the aggregate GDP growth rates. In other words, changes in the aggregate GDP growth rate largely stem from changes within industries rather than between them. Therefore, we use the fixed-weight aggregate as our benchmark series.

Second, there is significant variation in GDP growth rate, with a standard deviation of 4.06%. Much of this variation does not appear to be persistent, but the secular trend appears to

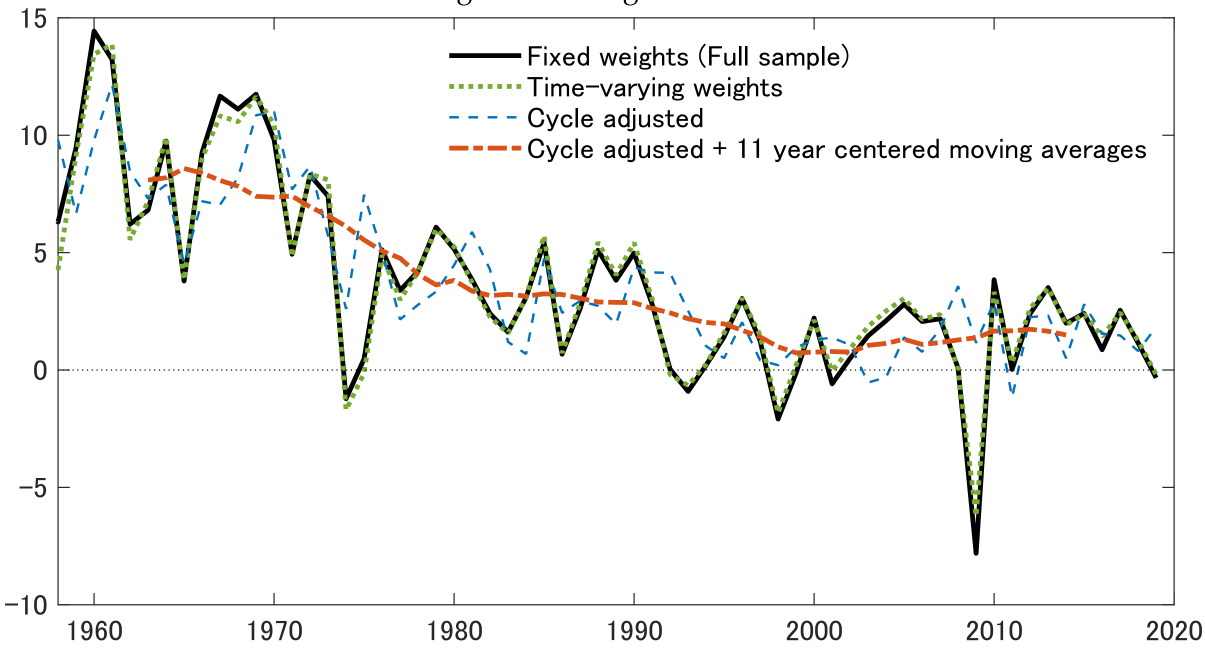
[3]Studies such as Carvalho et al. (2021) and Ito and Miyakawa (2022) stress the significance of amplification effects through production network using micro data.

[4]Fernández-Villaverde et al. (2023) argue that it is appropriate to use the GDP growth rate per working-age population instead of the GDP growth rate per capita when applying the standard growth model for aging economies.

[5]We report the details of data construction in Section 3.1.

be declining. The blue dotted line in Figure 1 reveals that short-term fluctuations remain even after removing the cyclical variation from the fixed-weight GDP growth rate by regressing a lead and a lag of changes in utilization rate.[6] To clarify the long-term trend, the red line in Figure 1 depicts centered 11-year moving averages of the GDP growth rate. Average annual trend growth rate varied over different time periods, with growth rates exceeding 8% in the high growth period that ends in 1970s, falling to 3% in the stable growth and "bubble" economy periods between the mid 1970s and 1990, declining further to nearly 1% in the 1990s and 2000s. The average growth rates by period in Table 1 also leads to the same conclusion: the trend growth rate of the aggregate GDP has declined over time, irrespective of the aggregation weights used in computing GDP.

Figure 1: GDP growth rates



Note: Average GDP growth rate per working-age population in percentage points at annual rate is presented. The GDP growth rate is a weighted average of industries' value added. "Fixed weights" represents a constant mean weighted average of full sample periods. "Cycle adjusted" represents a fixed-weights cycle-adjusted series using a lead and a lag of the utilization rate.

This study explores the source of this decline in the long-run GDP growth trends. To this end, we focus the analysis on the supply side of the economy because the interest of this study lies in the long term trend. Specifically, we consider the trend growth rate as a balanced growth path (BGP) that varies over time and identify how the industry's trend growth rates of TFP and labor have contributed to it. At first, in the next section, we describe the trend growth of TFP and labor. Then, we examine their aggregate implications.

[6] To remove the cyclical variations in the data, this study regresses each variable on a lead and a lag of changes in utilization rate and uses the residual as a cycle adjusted series. See Section 3.1 for the details of cycle adjustments.

Table 1: GDP growth rates by period

	Fixed weights Full sample period (1958-2019)		Time-varying weights		Fixed weights First 15 years (1958-1972)		Fixed weights Last 15 years (2005-2019)	
Cycle adjusted	No	Yes	No	Yes	No	Yes	No	Yes
1958-2019	3.7	3.8	3.7	3.8	3.4	3.5	3.8	3.9
1958-1973	9.0	8.3	8.8	8.1	8.9	8.2	8.8	8.1
1974-1990	3.3	3.5	3.3	3.4	3.0	3.1	3.5	3.6
1991-2000	0.8	1.7	0.9	1.8	0.4	1.3	1.2	2.1
2001-2019	1.1	1.3	1.3	1.6	0.8	1.0	1.4	1.6

Note: Average GDP growth rate per working-age population in percentage points at annual rate. The GDP growth rate is the weighted average of industries' value added. "Fixed weights" represents the constant mean weights of respective periods in parenthesis. "Cycle adjusted" represents the cycle-adjusted series using a lead and a lag of the utilization rate.

3 An empirical description of trend growth in TFP and labor

This study employs a statistical model to provide an empirical description of the growth rates of TFP and labor by industry in Japan. Specifically, we use industry-level TFP and labor growth rates, extract the trend components in the data, and apply a Bayesian statistical model to decompose these trend growth rates into the contributions of common and industry-specific factors.

3.1 Data

Our primary data source is the Japan Industrial Productivity Database (JIP), which is consistent with the EU-KLEMS data and is published by the Research Institute of Economy, Trade and Industry (RIETI).[7,8] These data are attractive for our purposes because they provide a consistent approach to constructing gross output and the primary inputs of capital and labor, as well as intermediate inputs, for a large number of industries. The JIP data are based on the Japanese System of National Accounts (JSNA) and consistently integrate industry data with input-output tables.

It is worth mentioning the definition of labor data in the JIP dataset. It is the quality-adjusted total labor hours, which reflects changes in both the number of workers and work hours per worker. Specifically, it is calculated as follows. Labor input is differentiated by gender, age, education, and employment status. Labor input growth is then defined as a weighted average of the growth in annual hours worked across all labor types, using the labor cost shares of each type as weights. By using the labor cost shares as weight, it reflects the

[7] See Fukao et al. (2007) and Fukao, ed (2021) for details on the JIP data.

[8] Inputs and outputs are converted to a per capita basis divided by the working-age population published by the Ministry of Internal Affairs and Communications.

quality of labor inputs.[9]

To examine long-term economic trends, this study links the JIP data with the other data and traces back to 1955. Specifically, the JIP data cover the period since 1970. Before 1970, we use the "Hitotsubashi University Institute of Economic Research Japan Industrial Productivity in High Growth Period (JIP) Database" (hereafter JIP-HGP) presented by Fukao and Makino (2021). The data cover the period since 1955, and are constructed in a complementary and consistent manner with the JIP data.

When linking multiple databases, we merge the industry classification in a consistent manner. Specifically, we re-aggregate JIP2015 and JIP2023 to the same 24 industries as the JIP-HGP. We follow Fukao and Makino (2021) for the matching of industries across databases. When merging industries, nominal data are aggregated by simple sums, while real data are aggregated as a Divisia index, following the procedure in Foerster et al. (2022) .[10] Finally, we obtain nominal and real values for output, labor input, capital input, intermediate input, and value-added TFP, from 1955 to 2019.[11] For the empirical analysis, we transform each series into its growth rate (log difference from the previous year).

Table 2 lists the average growth rates of value-added, labor, and TFP for each industry, and their standard deviations. There is a clear variation in growth rates across industries, highlighting the importance of analyzing individual industries rather than just aggregate data. Average growth rates of value-added range from -0.98% in Agriculture and forestry to 13.05% in Electrical machinery. In addition to Electrical machinery, high average growth rates are recorded mainly in the manufacturing sector, including Chemical (8.10%), Transportation machinery (6.46%), and precision machinery (5.66%), but also in some non-manufacturing sectors, such as Finance and insurance (5.14%) and Wholesale and retail trade (5.09%). Conversely, the Mining and Agriculture record negative growth, in line with the negative growth rate of labor.

In addition to these between variations, the within variations are also large. Specifically, the standard errors shown in the middle of the Table 2 are considerably large for many industries. Because the long-run economic growth is our primary focus, the high frequency fluctuations should be eliminated. To this end, we extract underlying trends from these noisy indicators.

Labor and TFP growth rates exhibit the similar tendency with the value-added growth rates. In terms of labor, in addition to Mining and Agriculture, Textiles (-2.96%) also record negative growth, with primary materials industries such as Pulp and paper, Petroleum and coal, Ceramics, soil and stone, and Primary metals all recording negative growth of around -1%. The main contributors to growth of labor are Real estate (4.56%), Service (2.20%), and Electrical machinery (1.84%), while positive growth is also seen in General machinery, Finance and insurance, and other industries, which in aggregate grow by 0.78%. As for TFP, high growth

[9] Details of the JIP data are provided in Appendix 3.1.

[10] Among the real value-added in the JIP database, some are published as negative values. We replace them with zero for aggregation.

[11] Since our interest is in the long-term economy, we set the estimation period to 2019, just before the Covid-19 crisis.

Table 2: Average growth rates of value added, labor and TFP by industry from 1958 to 2019

Industries	Average growth rate (cycle adjusted)			Standard deviation of average growth rate			Average share in value added
	Value added	Labor	TFP	Value added	Labor	TFP	
Agriculture	-0.98	-2.63	0.27	5.27	3.03	5.43	3.72
Mining	-1.47	-4.46	1.07	11.31	8.64	12.35	0.42
Foodstuffs	1.74	-0.89	1.00	5.51	3.50	5.41	3.53
Textiles	-0.24	-2.96	1.83	8.92	3.47	7.98	1.40
Pulp & paper	3.91	-0.89	3.37	9.08	3.18	7.34	0.73
Chemicals	8.10	-0.32	6.19	10.33	3.40	9.47	2.46
Petroleum & coal	1.50	-0.68	-0.65	20.93	4.50	20.19	1.26
Ceramics, soil & stone	3.10	-0.89	2.86	9.60	3.72	7.59	1.00
Primary metals	3.63	-1.02	2.11	15.40	4.69	13.68	2.49
Metal Products	4.19	0.56	2.94	10.09	4.37	7.47	1.35
General machinery	5.62	0.94	3.35	11.61	5.05	7.94	2.58
Electrical machinery	13.05	1.84	9.61	12.51	6.01	8.93	3.72
Transport machinery	6.46	0.67	3.95	10.91	4.80	9.66	2.88
Precision machinery	5.66	-0.46	4.36	11.76	4.71	9.18	0.57
Other manufacturing	2.72	-0.11	1.84	6.50	3.05	4.65	2.90
Construction	1.82	0.73	0.46	6.82	3.12	5.36	6.64
Utilities	3.73	0.26	0.28	6.78	4.17	6.47	3.04
Wholesale & retail trade	5.09	0.40	3.97	6.00	1.93	5.12	12.61
Finance & insurance	5.14	0.78	3.73	7.91	3.24	8.00	4.70
Real estate	2.12	4.56	-4.53	4.41	5.52	7.87	4.18
Transport & comm.	3.74	0.31	1.65	4.26	2.71	3.65	7.06
Service	3.01	2.20	-0.28	3.31	2.53	3.26	19.90
Other	2.17	0.71	0.37	2.14	2.76	2.77	4.39
Housing	2.77	-0.67	0.79	2.13	0.76	4.00	6.47
Aggregate	3.71	0.78	1.65	4.06	1.66	2.39	100.0

Note: Average growth rates are in percentage points. All data are the cycle-adjusted ones. Value added and labor are per working-age population basis. The aggregated values in the last row, we aggregate individual industry's TFP and labor growth rates with value-added share and cost share, respectively.

rates are recorded by Electrical machinery (9.61%), Chemicals (6.19%), Precision machinery (4.36%), Wholesale and retail trade (3.97%), and Transportation machinery (3.95%), as well as value-added. Other industries are also generally positive by a few percentage points, with the exception of Real estate (-4.53%) and Petroleum and coal and Service (-0.65%).

Finally, the rightmost column of the Table 2 presents the average share of value-added. The share of the non-manufacturing sector, shown at the bottom, is large, especially in Service (19.90%) and Wholesale and retail trade (12.61%). In contrast, the shares of General machinery (2.58%), Electrical machinery (3.72%), and Transportation machinery (2.88%) are relatively small. However, in the latter part of this study, we argue that the impact of these industries on the economy is non-negligible when we take production and investment networks into account.

3.2 Decomposition of trend growth rates of TFP and labor

The statistical framework consists of two steps. First, we extract low-frequency trends in the TFP and labor growth rates. Then, we estimate a Bayesian factor model to decompose the trend growth rates into common and industry-specific factors. Hereafter, we denote K and T as the number of industries and the length of sample periods, respectively.

3.2.1 Cycle adjustment and trend extraction of TFP and labor

First, we apply the adjustments of cyclical variations in the data. The values obtained in the previous section are volatile, and in some industries, much of the variability is related to business cycles. Because our interest lies in long-run trend variations, it is appropriate to remove cyclical variations in the raw growth rates. Specifically, we follow Fernald et al. (2017) in adjusting growth rates. For a measure of business cycles, we use the utilization rate published by the Ministry of Economy, Trade and Industry.[12]

Let $\Delta \ln \tilde{x}_{i,\tau}$ denote a growth rate of TFP or labor in industry i at date τ. We regress $\Delta \ln \tilde{x}_{i,\tau}$ on a lead and a lag of changes in the utilization rate u_τ,

$$\Delta \ln \tilde{x}_{i,\tau} = \beta_i^x(L)\Delta u_\tau + e_{i,\tau}^x. \tag{1}$$

where $\beta_i^x(L) = \beta_{i,1}^x L + \beta_{i,0}^x + \beta_{i,-1}^x L^{-1}$ is a lag operator, and $e_{i,\tau}^x$ is the residual.[13] Denoting $\hat{\beta}_i^x(L)$ as the OLS (ordinary least squares) estimator, we define the cycle-adjusted value of $\Delta \ln \tilde{x}_{i,\tau}$ as $\Delta \ln x_{i,\tau} \equiv \Delta \ln \tilde{x}_{i,\tau} - \hat{\beta}_i^x(L)\Delta u_\tau$.

Next, we extract low-frequency trends from the cycle-adjusted data. To estimate trend variations in data, Müllar and Watson (2008) propose regressing a time series data onto a constant and a set of low-frequency periodic functions. Specifically, denoting a cosine function on $s \in [0,1]$ with period $2/j$ as

$$\Psi_j(s) = \sqrt{2}\cos(js\pi),$$

we estimate parameters $\phi_{i,j}^x$ of the following equation by the OLS,

$$\Delta \ln x_{i,\tau} = \sum_{j=1}^{q} \phi_{i,j}^x \Psi_{j,\tau} + \zeta_{i,\tau}^x, \tag{2}$$

where $\Psi_{j,\tau} \equiv \Psi_j((\tau - 1/2)/T)$ for $\tau = 1, ..., T$; $\zeta_{i,\tau}^x$ is the residual, respectively.

The projected variable of the above regression corresponds to the $\Delta \ln x_{i,\tau}$'s low-frequency movements with periodicities longer than $2T/q$. This approach regards a trend in data as a weighted average of periodic functions, taking estimated coefficients as weights. Müllar and Watson (2015) stress that the above low-frequency weighted averages of periodic functions have an advantage over other filters (*e.g.* HP filter or BK filter) in effectively summarizing the trend information from highly persistent time-series data with small samples.[14]

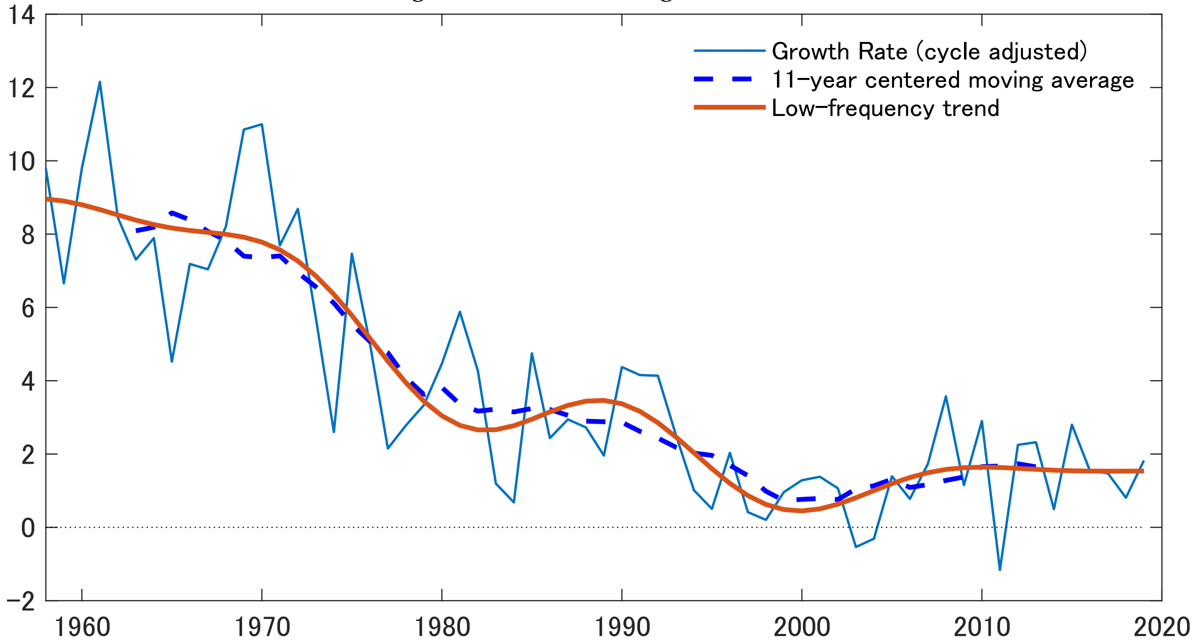
In our application that has the data from 1958 to 2019 ($T = 62$), we set $q = 8$, following Foerster et al. (2022). Accordingly, the estimated values are low-frequency trends longer than

[12]Since the utilization rate coverage used here is only for manufacturing, we assume that the non-manufacturing sector has roughly the same cyclical resource utilization as the manufacturing sector.

[13]For notational simplicity, we omit the constant term from (1) and (2).

[14]Müllar and Watson (2008) point out that the low-frequency trigonometric weighted averages cannot eliminate some leakage of high-frequency movements. Thus, the pre-treatment of cycle adjustments makes our analysis more prudent.

Figure 2: Trend GDP growth rates



Note: Blue solid line represents the cycle-adjusted aggregate GDP growth rates. Red and blue dotted lines represent the low-frequency triogonometric weighted average of GDP growth rate and the 11-year centered moving average of it, respectively.

$15.5(= 2 \times 62/8)$ years. For reference, Figure 2 presents an application of this method to the aggregate GDP.[15] The trend depicted by the blue line captures the long-term trend in the actual data of the blue solid line. The estimated trend is similar to the 11-year central moving average of the red line.

Figures 3 and 4 show the cycle adjusted growth rates of labor and TFP, respectively, for each of the 24 industries, along with their low-frequency trends. Labor and TFP growths show common movements for some periods, while they show industry-specific movements for other periods. Most of the series are highly noisy, but these high frequency fluctuations appear to be short lived. Therefore, it seems that the long-term trends are not significantly affected by these transient factors.[16]

In terms of labor, many industries experienced high growth rates in the 1960s, a high-growth period (General machinery, Electrical machinery, Chemicals, Construction, Wholesale and retail trade, and Finance and insurance). After that, they experienced a decline in labor growth rates, but the timing of the decline varied from industry to industry. Some industries, such as General machinery, Electrical machinery, and Construction, saw their labor growth

[15]The GDP growth rate depicted in Figure 2 does not correspond to the JSNA's GDP growth rate, due to several reasons. First, it represents the growth rate per working-age population instead of the raw growth rate. Second, it is the aggregate of the value-added of 24 industries. Third, we apply the cycle adjustment to the growth rate per working-age population using parameters estimated with the utilization rate of whole sample period. Consequently, it should be cautious about directly comparing the corresponding trend growth rate with the potential growth rate based on the JSNA's GDP.

[16]We use the different low frequency trend longer than 20.7 years ($q = 6$) and confirm that the main conclusions are robust to this change.

rates decline throughout the 1970s, while others, such as Chemicals, saw their growth rates decline slowly throughout the 1980s. On the other hand, Wholesale and retail trade and Finance and insurance maintained high labor growth rates throughout the 1980s. The 1990s saw a decline in the growth rate of labor in many industries, including those listed above, and the background is discussed in a later section. Many industries have recovered their growth rates since then, but some industries, such as Transportation machinery, Wholesale and retail trade, and Finance and insurance, have experienced declines since the 2010s.

As for TFP, similar to Japan's economic growth rate, many industries gradually decreased their growth rates from the 1960s to the 2000s (*e.g.*, General machinery, Electrical machinery, Transportation machinery, and Wholesale and retail trade), although the extent of the decline in growth rates varied by industry. After the 2000s, TFP growth rates remained close to zero percent in many industries. However, there are exceptions, such as Electrical machinery, where the growth rate has continued to decline since 2000. On the other hand, some industries, such as Construction and Financial insurance, have gradually increased their growth rates.

In a nutshell, some TFP and labor movements appear to be industry-specific, while others appear to be common to industries. In the following sections, we quantify these factors and explore the aggregate implications of these industry commonalities and differences.

3.2.2 Estimation of common and industry-specific factors in TFP and labor

The results in the previous subsection reveal that the industry's TFP and labor appear to comove with those of other industries in some part but idiosyncratic variations are also non-negligible. To quantify the common and idiosyncratic factors in low frequency trends of $\Delta \ln l_{i,\tau}$ and $\Delta \ln a_{i,\tau}$, we consider the following factor model,

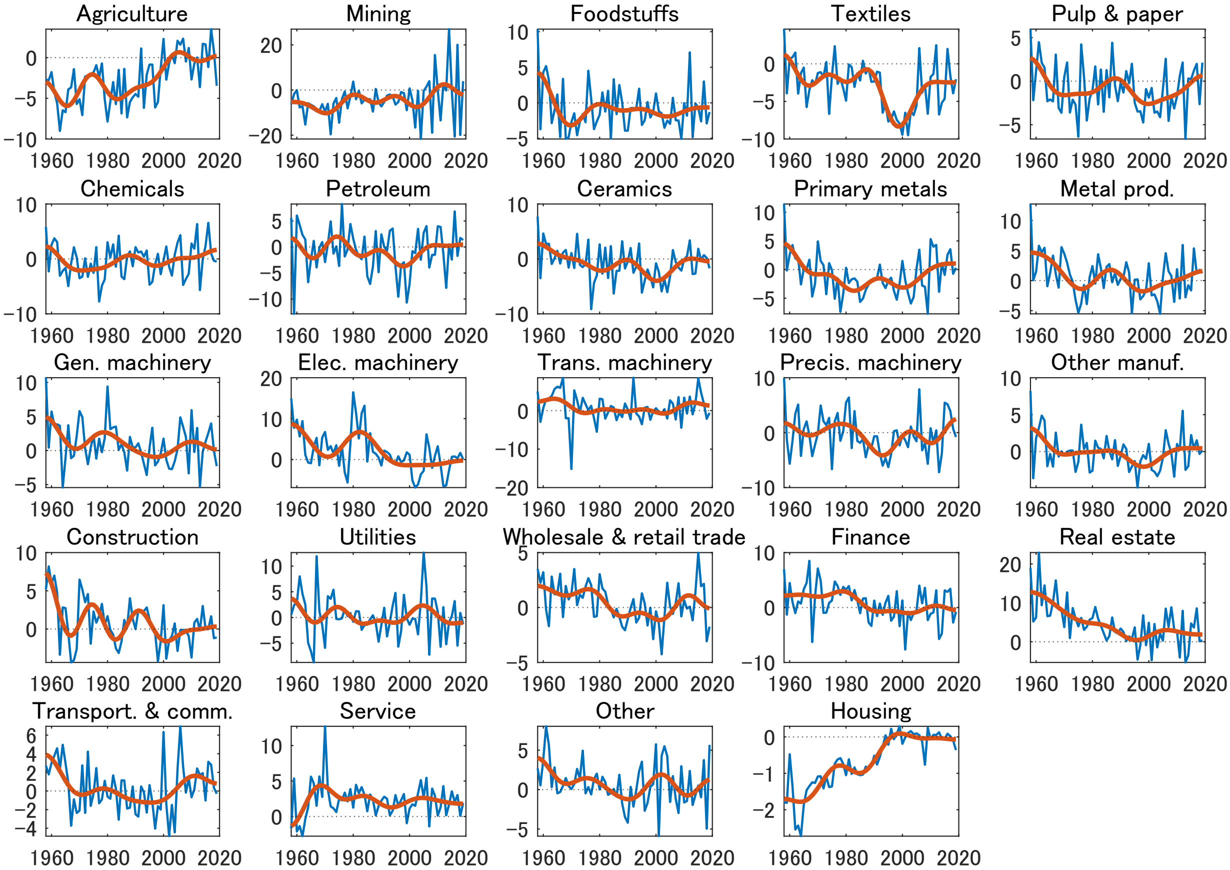
$$\begin{bmatrix} g^l_{i,\tau} \\ g^a_{i,\tau} \end{bmatrix} = \begin{bmatrix} \lambda^l_i & 0 \\ 0 & \lambda^a_i \end{bmatrix} \begin{bmatrix} f^l_\tau \\ f^a_\tau \end{bmatrix} + \begin{bmatrix} \epsilon^l_{i,\tau} \\ \epsilon^a_{i,\tau} \end{bmatrix} \tag{3}$$

where $g^l_{i,\tau}$ and $g^a_{i,\tau}$ are low frequency trends of $\Delta \ln l_{i,\tau}$ and $\Delta \ln a_{i,\tau}$; f^l_τ and f^a_τ are unobservable common factors of labor and TFP; λ^l_i and λ^a_i are respective factor loadings; $\epsilon^l_{i,\tau}$ and $\epsilon^a_{i,\tau}$ are sector-specific disturbances.

We estimate the model with Bayesian methods.[17] The priors are relatively uninformative except for the factor loadings $\boldsymbol{\lambda}^{\boldsymbol{l}} = \{\lambda^l_1, ..., \lambda^l_K\}$ and $\boldsymbol{\lambda}^{\boldsymbol{a}} = \{\lambda^a_1, ..., \lambda^a_K\}$ because it is difficult to separately identify the scale of factor and factor loadings. As for the labor growth, we assume $\boldsymbol{\omega}_{\boldsymbol{l}}' \boldsymbol{\lambda}^{\boldsymbol{l}} = 1$ where $\boldsymbol{\omega}_{\boldsymbol{l}}$ is the vector of average industry shares of labor. This restriction normalizes the size of factor movements and facilitates the interpretation: a one unit of increase in f^l_τ

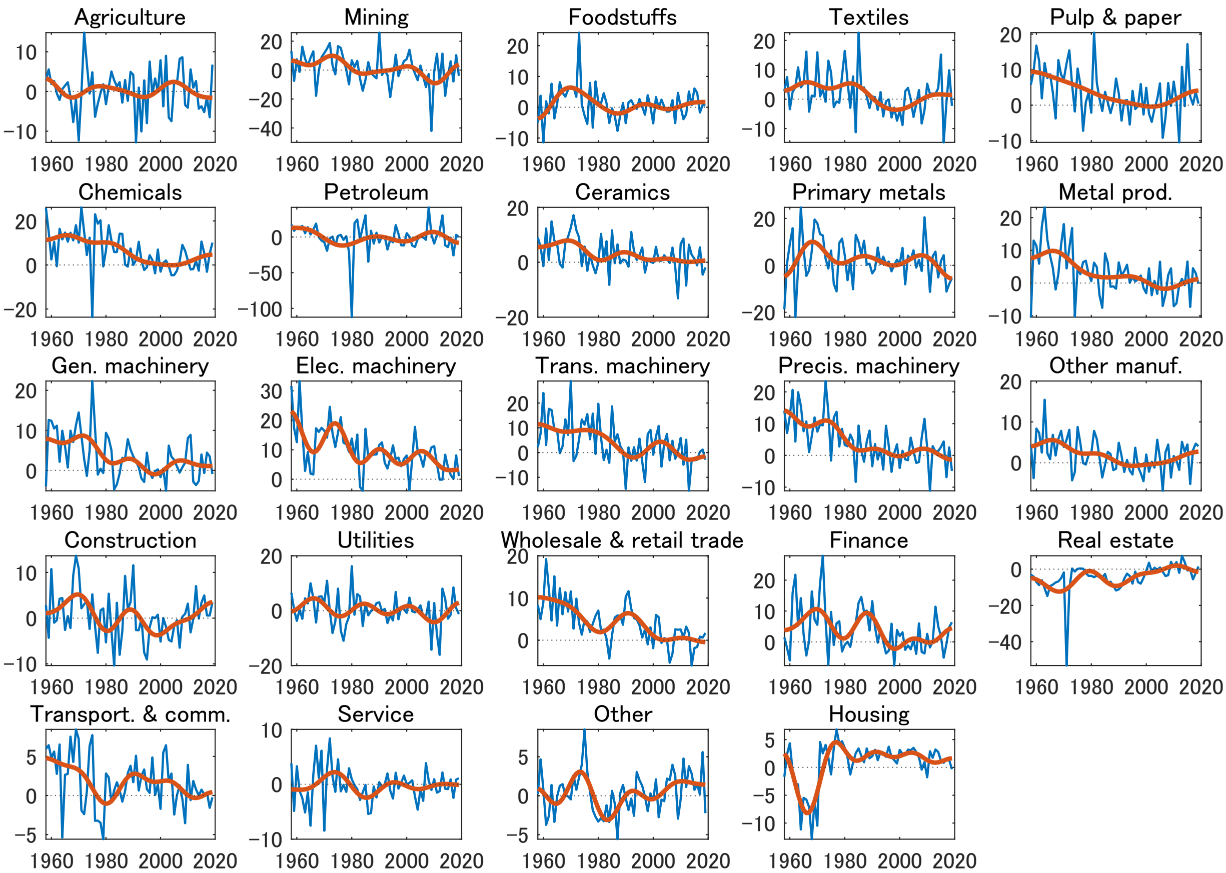
[17] Using the trend variations obtained from (2), we can estimate the model and decompose long-term trends into industry common factors and industry-specific factors. Notably, Foerster et al. (2022) do not directly estimate this model but rather convert (3) into a low frequency factor model by exploiting the representation of long-term trends with periodic functions and estimate it. This study follows their approach. Appendix B provides an overview of this approach.

Figure 3: Labor growth rates by industries (percentage points at an annual rate)



Note: Blue and red lines represent the cycle-adjusted labor growth rates by industries and their corresponding trends as low-frequency triogonometric weighted averages.

Figure 4: TFP growth rates by industries (percentage points at an annual rate)



Note: Blue and red lines represent the cycle-adjusted TFP growth rates by industries and their corresponding trends as low-frequency triogonometric weighted averages.

corresponds to a one unit increase of $\Delta \ln l_\tau$ in the long run. The prior for $\boldsymbol{\lambda^l}$ is $\boldsymbol{\lambda^l} \sim N(\mathbf{1}, \boldsymbol{P_l})$, where $\mathbf{1}$ and $\boldsymbol{P_l}$ are a vector of 1s and $\boldsymbol{P_l} = \eta^2[\boldsymbol{I} - \boldsymbol{\omega_l}(\boldsymbol{\omega_l'}\boldsymbol{\omega_l})^{-1}\boldsymbol{\omega_l'}]$. The parameter η regulates the speed of reversion of the estimates of λ_i^l to their mean of unity. We set $\eta = 1$ in the benchmark case and examine the sensitivity to other values of η in the robustness check section 4.5. As for the TFP growth, We use an analogous prior for $\boldsymbol{\lambda^a}$.

3.3 Results of the decomposition

This subsection reports estimated parameters by industry and the decomposition into common and industry-specific factors. In this estimation, the number of draws is 550,000 and the first 50,000 draws are discarded as burn-in. Table 3 summarizes the posterior medians of factor loadings with 68% credible intervals. It also reports to what extent the trend growth variations are attributable to common factors as a posterior distribution of R^2.

As for the factor loadings, Textile and Ceramics are the largest values for labor and exceed 2, whereas Housing and Services are the smallest. Metal products and Precision machinery are the largest values for TFP, while Housing and Agriculture are the smallest. Reflecting that the number of sample periods is limited, the credible intervals are considerably wide.

The explanatory power of common factors varies across industries. For labor, the common factor explains more than 70% of variations in Other manufacturing, Metal products, and Ceramics, while it explains about 10% in Electric machinery and Precision machinery, and only 3% in Services and Agriculture. For TFP, the explanatory power of common factors is slightly lower than that of labor. The common factor explains about 73 % of variations in Pulp and paper and 65 % in Other manufacturing, with only three industries exceeding 50%. On the other hand, many industries such as Agriculture, Mining, Petroleum, Primary metals, Electrical machinery, Transportation machinery, Utilities, Real estate, Others, and Housing have an explanatory power of less than 10 %. Further, the right column presents the correlations among labor and TFP factors. It exhibits negative correlations in some industries. In particular, Foodstuffs and Mining have stronger negative correlations, -0.60 and -0.56, respectively.

The last row of Table 3 reports the aggregated values, where, following Hulten (1978), we aggregate individual industry's TFP and labor growth rates with value-added share and cost share, respectively. Accordingly, by definition, factor loadings are 1.0 for both labor and TFP. The explanatory power is higher for aggregates than for each industry because Lucas's diversification argument—industry-specific factors cancel each other out and are washed out in aggregates—holds in some parts, and the explanatory power of the common factors tends to be greater in aggregates. Consequently, approximately two-thirds of the variations in TFP and labor are attributable to the common factors. Compared to the case of US in Foerster et al. (2022), the explanatory power of the TFP common factor is higher in Japan (0.59 in Japan and 0.30 in US), while that of the labor common factor is not different among Japan and US (0.68 in Japan and 0.67 in US).

It is worth stressing that we cannot directly deduce the role of industry-specific trends in the aggregate GDP from the findings reported in the "Aggregate" row in Table 3. This is because industry-specific trends affect the aggregate GDP not merely through the direct channel. Some industries are input supplier and are connected with other industries through production and investment networks. Consequently, these industries can be more influential beyond the value-added share in the aggregate GDP. We will examine this point in the next section.

Figure 5 illustrates a historical decomposition of trend growth rates in the aggregate labor and TFP. Figure 5 (a) and (c) depict the low-frequency trends in the aggregated labor and TFP. Figure 5 (b) and (d) depict the decomposition of the trends into common and industry-specific factors. Figure 5 (b) suggests that the labor common factor causes the high labor growth in the 1960s and low labor growth in the mid 1990s. The former are associated with the changes in demographics, and the latter reflects the implementation of labor policies for reduced working hours, such as the introduction of a 40-hour workweek. Figure 5 (d) suggests that the contribution of common factor is more evident in the low-frequency movements in the TFP growth rates. During the high growth periods that ended in 1973, the common TFP factor significantly contributes to the low-frequency TFP growth, though it contributed negatively in the 1990s and 2000s. It is interesting that the low TFP growth in the last 10 years are largely attributable to industry specific factors, amidst the improvement of common factors.

Figure 6 and 7 report the decompositions of the labor and TFP growth rates by industry[18]. These figures clearly show that the industry-specific factors significantly contribute to individual industry's labor and TFP trend growth rates. In conjunction with Figure 5, this result illustrates that Lucas's diversification argument is, to some extent, applicable to Japan's industry data.[19]

4 The aggregate implications of industries' trends

The analyses in the previous section show that both common and industry-specific factors influence the trends in TFP and labor. This raises a following question: how much of the aggregate GDP's trend growth is attributable to common factors, and how much to industry-specific factors?

To address this question, additional information regarding the economic structure is necessary. For instance, one might consider whether simply extracting the common components of industries' GDP growth is sufficient. If industries were isolated and did not influence each other, an industry-specific factor would influence only the own industry's value added, and thus, the co-movements among industries would be all attributable to the industry-common factors. However, industries do influence one another. Moreover, their interactions occur not only through production networks of intermediates but also through investment networks of capital goods, as emphasized in vom Lehn and Winberry (2022). In such scenarios, industry-specific

[18] 68 % credible intervals are shown in Figure 18 and 19 in the Appendix.

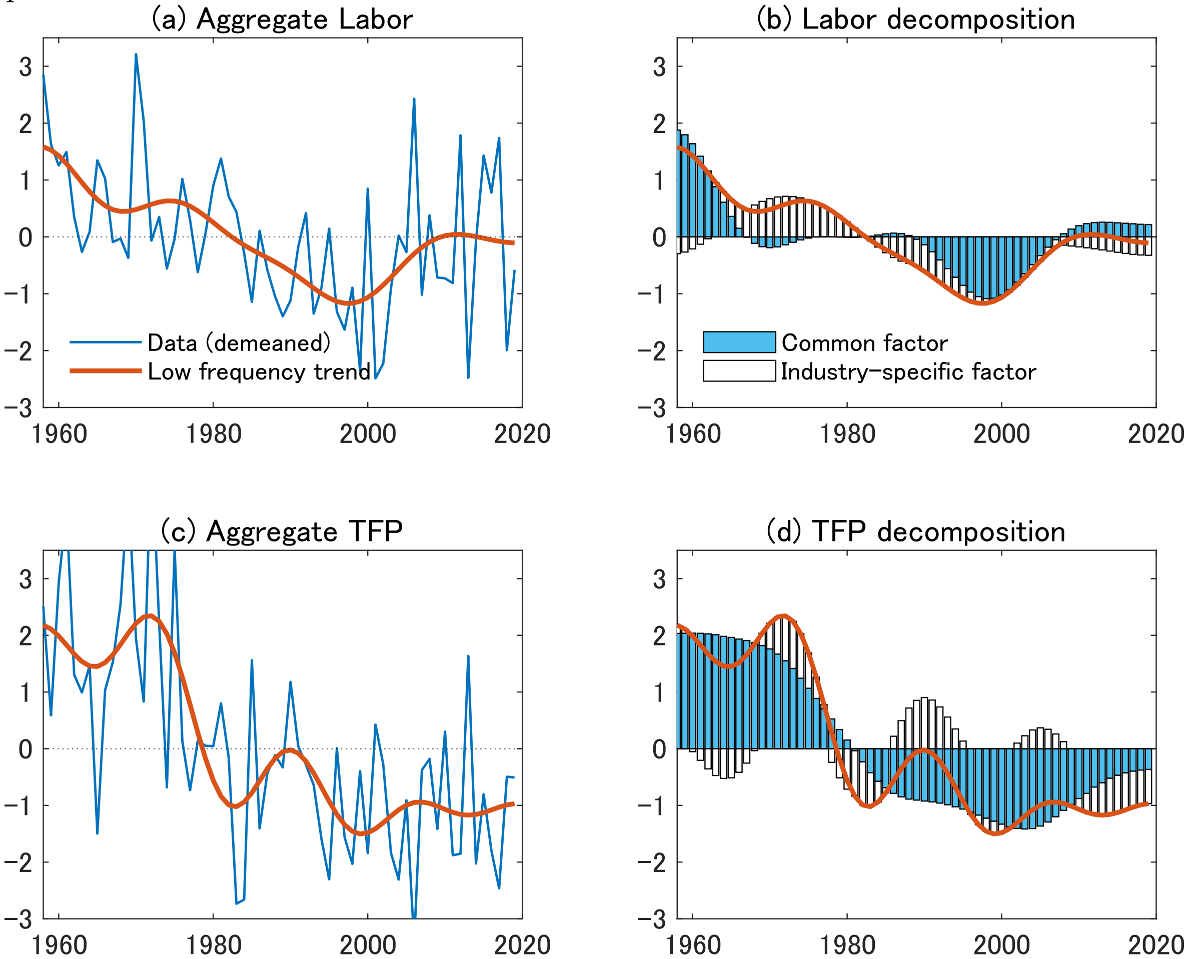
[19] This tendency also appears in US industry data as reported in Foerster et al. (2022).

Table 3: Estimation results

Industry	Factor loadings: λ^l and λ^a Labor	TFP	Relative explanatory power of common factor: R^2 Labor	TFP	Correlation (Labor, TFP)
1. Agriculture	0.51	0.20	0.03	0.04	0.26
	(-0.22, 1.24)	(-0.29, 0.78)	(0.00, 0.15)	(0.00, 0.17)	(0.02, 0.59)
2. Mining	0.90	1.33	0.03	0.08	-0.56
	(0.07, 1.71)	(0.56, 2.04)	(0.00, 0.15)	(0.01, 0.27)	(-0.77, -0.26)
3. Foodstuffs	0.81	1.27	0.17	0.14	-0.60
	(0.22, 1.40)	(0.60, 1.99)	(0.02, 0.52)	(0.03, 0.36)	(-0.85, -0.22)
4. Textiles	2.11	1.12	0.49	0.14	0.53
	(1.47, 2.69)	(0.33, 1.75)	(0.20, 0.76)	(0.02, 0.40)	(0.17, 0.79)
5. Pulp and paper	1.31	1.95	0.53	0.73	0.37
	(0.71, 1.84)	(1.07, 2.67)	(0.16, 0.81)	(0.24, 0.97)	(0.01, 0.89)
6. Chemicals	1.57	1.39	0.53	0.15	-0.14
	(1.08, 2.07)	(0.42, 2.24)	(0.24, 0.76)	(0.02, 0.42)	(-0.49, 0.21)
7. Petroleum	1.64	1.03	0.43	0.01	-0.29
	(1.01, 2.27)	(0.13, 1.91)	(0.16, 0.69)	(0.00, 0.06)	(-0.64, -0.02)
8. Ceramics	2.04	1.04	0.72	0.20	0.46
	(1.58, 2.49)	(0.32, 1.64)	(0.44, 0.88)	(0.02, 0.63)	(0.16, 0.72)
9. Primary metals	1.58	1.06	0.30	0.06	-0.19
	(0.91, 2.23)	(0.29, 1.83)	(0.07, 0.63)	(0.01, 0.21)	(-0.50, -0.00)
10. Metal products	2.35	2.00	0.71	0.46	0.39
	(1.80, 2.86)	(1.20, 2.57)	(0.43, 0.87)	(0.15, 0.84)	(0.14, 0.82)
11. General machinery	1.72	1.75	0.65	0.53	-0.01
	(1.23, 2.21)	(1.14, 2.31)	(0.33, 0.85)	(0.17, 0.80)	(-0.35, 0.35)
12. Electrical machinery	1.89	1.51	0.16	0.09	-0.04
	(1.04, 2.66)	(0.68, 2.33)	(0.03, 0.42)	(0.01, 0.31)	(-0.30, 0.17)
13. Transportation machinery	1.12	1.39	0.40	0.08	-0.24
	(0.62, 1.61)	(0.41, 2.31)	(0.09, 0.70)	(0.01, 0.35)	(-0.55, -0.02)
14. Precision machinery	1.06	1.83	0.14	0.26	-0.02
	(0.38, 1.74)	(0.89, 2.73)	(0.02, 0.43)	(0.04, 0.71)	(-0.34, 0.24)
15. Other manufacturing	1.77	1.36	0.99	0.65	0.54
	(1.54, 2.01)	(0.84, 1.80)	(0.95, 1.00)	(0.24, 0.86)	(-0.31, 0.91)
16. Construction	1.73	1.29	0.35	0.21	-0.01
	(1.06, 2.34)	(0.68, 1.95)	(0.11, 0.63)	(0.04, 0.48)	(-0.34, 0.30)
17. Utilities	0.69	0.75	0.10	0.08	-0.31
	(0.09, 1.33)	(0.18, 1.34)	(0.01, 0.34)	(0.01, 0.28)	(-0.60, -0.01)
18. Wholesale and retail trade	0.99	1.58	0.41	0.20	-0.20
	(0.59, 1.40)	(0.84, 2.28)	(0.13, 0.71)	(0.04, 0.50)	(-0.54, 0.02)
19. Finance and insurance	0.55	1.47	0.07	0.12	-0.18
	(0.06, 1.09)	(0.67, 2.17)	(0.01, 0.28)	(0.02, 0.34)	(-0.48, 0.01)
20. Real estate	1.50	0.51	0.19	0.02	-0.14
	(0.84, 2.18)	(-0.48, 1.48)	(0.04, 0.45)	(0.00, 0.10)	(-0.44, 0.11)
21. Transportation and communication	1.67	0.71	0.69	0.10	-0.19
	(1.27, 2.04)	(0.15, 1.30)	(0.41, 0.86)	(0.01, 0.33)	(-0.55, 0.07)
22. Services	0.11	0.61	0.03	0.14	0.11
	(-0.34, 0.56)	(0.21, 1.18)	(0.00, 0.13)	(0.02, 0.40)	(-0.13, 0.47)
23. Others	0.86	0.60	0.16	0.09	0.00
	(0.30, 1.44)	(0.04, 1.34)	(0.02, 0.47)	(0.01, 0.32)	(-0.29, 0.28)
24. Housing	-0.29	0.08	0.17	0.02	0.46
	(-0.43, -0.15)	(-0.63, 0.91)	(0.04, 0.40)	(0.00, 0.09)	(0.22, 0.75)
Aggregate	1.00	1.00	0.68	0.59	0.15
	-	-	(0.48, 0.83)	(0.40, 0.75)	(-0.13, 0.42)

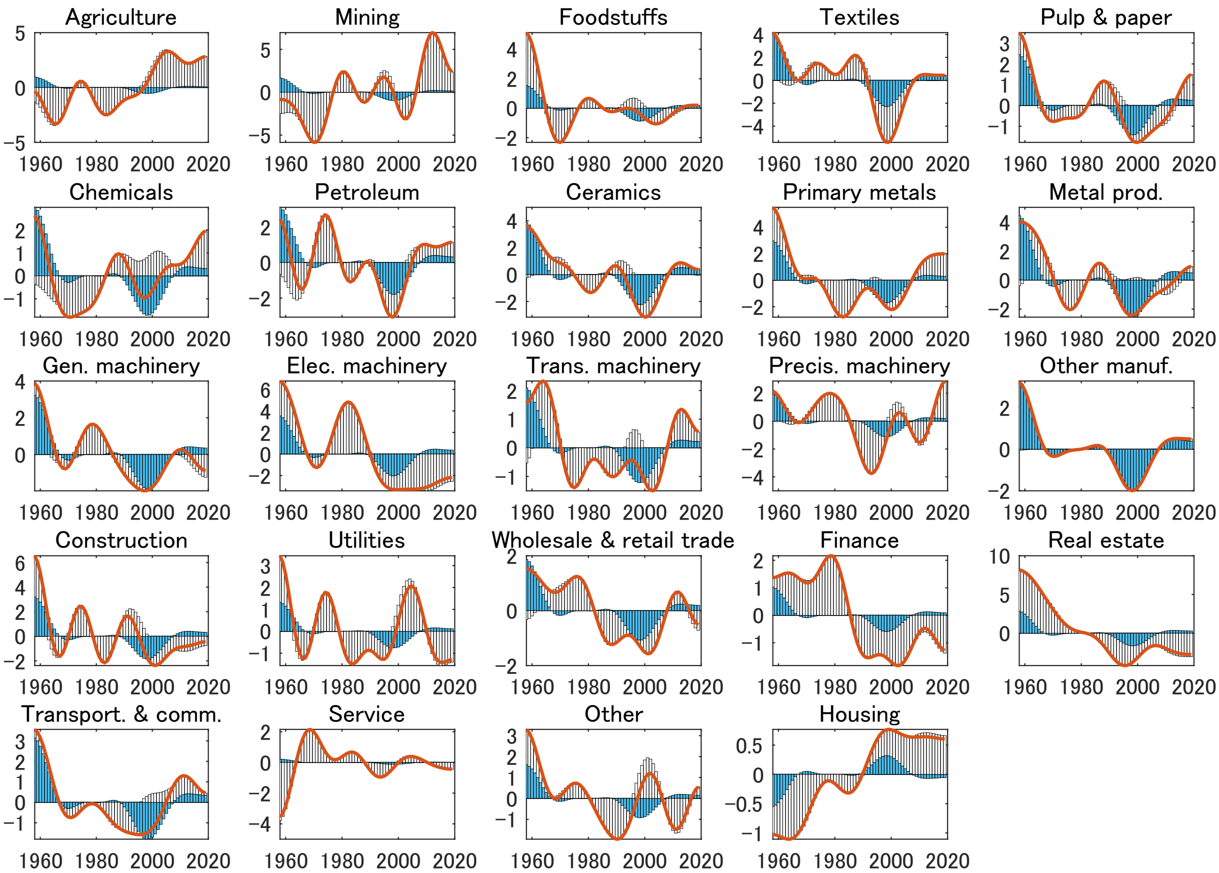
Note: The estimates are posterior medians, with 68% credible intervals shown in parentheses. The fourth and fifth column report the relative explanatory power of common factor against industry-specific factor. The correlation column reports the correlation of industry-specific factors for rows of industries and that of common factors for rows of “Aggregate”.

Figure 5: Aggregate labor and TFP growth rates: decomposition into common and industry-specific factors



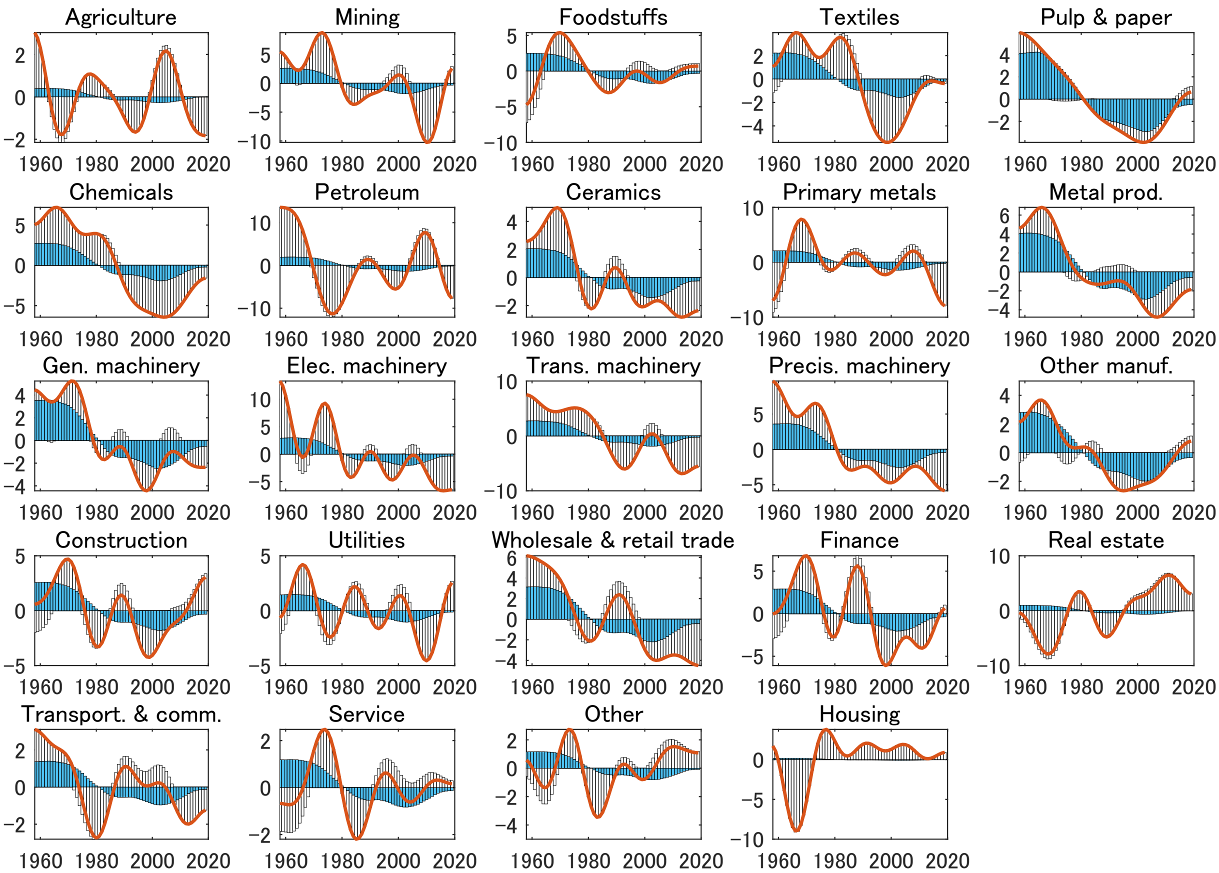
Note: (a) and (c) show the growth rates (deviation from average) and the low-frequency trend. The other panels show the low-frequency trend (red line) and its decomposition into changes due to the common factor (blue bars) and industry-specific factors (white bars).

Figure 6: Labor trend growth and decomposition into common and industry-specific factors



Note: Red lines, blue bars, and white bars represent the low-frequency labor trend growth rate in percentage points, the contribution of common factor, and that of industry-specific factor, respectively.

Figure 7: TFP trend growth and decomposition into common and industry-specific factors



Note: Red lines, blue bars, and white bars represent the low-frequency TFP trend growth rate in percentage points, the contribution of common factor, and that of industry-specific factor, respectively.

fluctuations of TFP and labor in a single industry can affect other industries' value added and cause co-movements among industries. Therefore, it is imperative to consider inter-industry linkages when decomposing the aggregate growth rate into the contributions of common and industry-specific factors.

To be specific, following Foerster et al. (2022), this study utilizes a multi-industry growth model that incorporates production and investment networks as additional information about the economic structure. It then clarifies the extent to which the common and industry-specific factors of TFP and labor contribute to the GDP trend growth rate.

4.1 A multi-industry model of production and investment networks

This subsection presents the economic environment. The model is a multi-industry neoclassical growth model, which shares features with Long and Plosser (1983), Acemoglu et al. (2012), and Foerster et al. (2022). Following Foerster et al. (2022), we explain the specific setup of the model.

4.1.1 Households

Identical and infinitely-lived households enjoy consumption c_τ, supply labor inputs to industry i, $l_{i,\tau}$ for $i \in [1, 2, ..., K]$, own capital stocks used in industry i, $k_{i,\tau}$, and rent these to producers in competitive markets. A representative household maximizes its lifetime utility,

$$\sum_{\tau=t}^{\infty} \beta^{\tau-t} \left[\ln\left(c_\tau\right) - \sum_{i=1}^{K} \frac{l_{i,\tau}^{1+\xi}}{1+\xi} \right],$$

subject to a budget constraint, $b_{\tau+1} + p_\tau^c c_\tau = (1+r_\tau)b_\tau + w_\tau \sum_{j=1}^{K} l_{i,\tau} + \sum_{i=1}^{K} r_{i,\tau}^k k_{i,\tau} - \sum_{i=1}^{K} p_{i,\tau}^u u_{i,\tau}$, where p_τ^c, $p_{i,\tau}^u$, w_τ, $r_{i,\tau}^k$, and $u_{i,\tau}$ denote the consumption price index, the industry i' investment price index that is used for investment in a i industry, wages, the rental costs of capital, and investment in industry i's capital stocks, respectively. $\beta \in (0, 1)$ and ξ are a discount factor and the Frisch elasticity, respectively. Each industry's capital stock evolves according to $k_{i,\tau+1} = (1-\delta_i)\, k_{i,\tau} + u_{i,\tau}$ where $\delta_i \in (0, 1)$ is the depreciation rate. We assume that the population growth rate is zero.

Solving the first order conditions yields the rental cost of capital,

$$r_{i,\tau+1}^k = \left\{ p_{i,\tau+1}^u \left[\frac{1+r_{\tau+1}}{p_{i,\tau+1}^u / p_{i,\tau}^u} - (1-\delta_i) \right] \right\}. \tag{4}$$

4.1.2 Firms

A representative producer in an industry $i \in \{1, 2, ..., K\}$ produces a good $y_{i,\tau}$ according to the following Cobb-Douglas production function,

$$y_{i,\tau} = \left[a_{i,\tau} \left(k_{i,\tau}\right)^{\alpha_{u,i}} \left(l_{i,\tau}\right)^{1-\alpha_{u,i}}\right]^{1-\alpha_{m,i}} \left(m_{i,\tau}\right)^{\alpha_{m,i}}, \tag{5}$$

where $a_{i,\tau}$ and $m_{i,\tau}$ are the i-th industry's productivity index and intermediate inputs, respectively. The growth rate of productivity is $a_{i,\tau}/a_{i,\tau-1} = 1 + g_{i,\tau}$.

Products are used for either fulfilling the final demand or intermediate inputs. The final demand consists of consumption and investment, which are composite indices of industry products,

$$c_\tau = \prod_{j=1}^{K} \left(\frac{z_{c,j,\tau}}{\omega_{c,j}}\right)^{\omega_{c,j}}, \quad u_{i,\tau} = \prod_{j=1}^{K} \left(\frac{z_{u,i,j,\tau}}{\omega_{u,i,j}}\right)^{\omega_{u,i,j}},$$

where $z_{c,j}$ and $z_{u,i,j}$ denote goods produced in industry j and used for consumption and investment in industry i, respectively. $\omega_{c,j} \in [0, 1]$ and $\omega_{u,i,j} \in [0, 1]$ are industry j's final-demand share in consumption and investment in industry i, satisfying $\sum_{j=1}^{K} \omega_{c,j} = 1$ and $\sum_{j=1}^{K} \omega_{u,i,j} = 1$. $\omega_{u,i,j}$ is an input-share parameter of investment input-output matrix $\boldsymbol{\Omega_u}$. The corresponding price indices are $p^c_\tau = \prod_{j=1}^{K} \left(p_{j,\tau}\right)^{\omega_{c,j}}$ and $p^u_{i,\tau} = \prod_{j=1}^{K} \left(p_{j,\tau}\right)^{\omega_{u,i,j}}$. We assume that the consumption price index is a numeraire in this economy: $p^c_\tau = 1$.

The intermediate inputs used in industry i are also a composite index of industry products,

$$m_{i,\tau} = \prod_{j=1}^{K} \left(\frac{z_{m,i,j,\tau}}{\omega_{m,i,j}}\right)^{\omega_{m,i,j}},$$

where $z_{m,i,j}$ and $\omega_{m,i,j} \in [0, 1]$ denote goods produced in industry j and used for industry i's intermediate input, and an input-share parameter of input-output matrix $\boldsymbol{\Omega_m}$, respectively. The input shares satisfy $\sum_{j=1}^{K} \omega_{m,i,j} = 1$ for any i. The corresponding price index of an industry i's intermediate inputs is $p^m_{i,\tau} = \prod_{j=1}^{K} (p_{j,\tau})^{\omega_{m,i,j}}$.

Finally, gross outputs in industry i, $y_{i,t}$, suffice for the demand identity,

$$y_{i,\tau} = y^d_{i,\tau} = z_{c,i,\tau} + \sum_{j=1}^{K} z_{u,j,i,\tau} + \sum_{j=1}^{K} z_{m,j,i,\tau}.$$

4.2 Growth accounting on the BGP

To explore the source of GDP's trend growth, we perform the growth accounting of the aggregate value-added on the BGP. The value added is defined as follows: $p^{va}_{i,\tau} y^{va}_{i,\tau} \equiv p_{i,\tau} y_{i,\tau} - p^m_{i,\tau} m_{i,\tau}$. Its production function is derived as,[20]

$$y^{va}_{i,\tau} = \bar{\alpha}_{m,i} A_{i,\tau} k^{\alpha_{u,i}}_{i,\tau}, \tag{6}$$

where

$$\Delta \ln A_{i,\tau} = \underbrace{\Delta \ln a_{i,\tau}}_{\text{TFP growth}} + (1-\alpha_{u,i}) \underbrace{\Delta \ln l_{i,\tau}}_{\text{Labor growth}},$$

and $\bar{\alpha}_{m,i} \equiv \alpha_{m,i}^{\alpha_{m,i}/(1-\alpha_{m,i})}$.

Conditioning on the observed behavior of TFP and labor inputs, this study examines their effects on the aggregate GDP growth. It is, of course, possible in theory to endogenize the allocation of labor, though the growth accounting expressions are largely unchanged. However, it is difficult to find observable labor-related shocks that drive allocation of labor among industries. Therefore, this study follows Foerster et al. (2022)'s strategy to treat labor inputs as exogenous forcing variables.

Now, we denote the gross output's growth rate as $g^y_{i,\tau}$. The demand identify implies the products of this industry, $c_{i,\tau}$, $z_{u,i,\tau}$, and $z_{m,i,\tau}$, also grow at the same rate on the BGP. As for the supply side, because intermediates and investments are the composite of other industries' products, the intermediates' and investments' growths of industry i, $g^m_{i,\tau}$ and $g^k_{i,\tau}$ are expressed as follows,

$$g^m_{i,\tau} = \sum_{j=1}^{K} \omega_{m,i,j} g^y_{j,\tau}; \quad g^k_{i,\tau} = \sum_{j=1}^{K} \omega_{u,i,j} g^y_{j,\tau}.$$

Denoting $\boldsymbol{g}^x_\tau$ is the vector of x's growth rate, the growth of intermediates and capitals are expressed as follows,

$$\boldsymbol{g}^m_\tau = \boldsymbol{\Omega}_m \boldsymbol{g}^y_\tau; \quad \boldsymbol{g}^k_\tau = \boldsymbol{\Omega}_u \boldsymbol{g}^y_\tau, \tag{7}$$

where $\boldsymbol{\Omega}_m$ and $\boldsymbol{\Omega}_u$ are the input-output matrix and capital flow matrix, respectively. In this study, we refer to the network structure represented by the input-output matrix of intermediates as the "production network," and the network structure represented by the capital flow matrix as the "investment network". Further, from (6), the vector of value added growth is expressed as follows,

$$\boldsymbol{g}^{va}_\tau = \boldsymbol{g}^A_\tau + \boldsymbol{\alpha}_u \boldsymbol{g}^k_\tau, \tag{8}$$

where $\boldsymbol{g}^A_\tau$ and $\boldsymbol{\alpha}_u$ are the vector of $A_{i,\tau}$'s growth rates and a diagonal matrix of $\alpha_{u,i}$, respectively.

[20] A producer's optimality condition leads to the equilibrium usage of intermediates as follows,

$$m_{i,\tau} = \alpha_{m,i} \frac{p_{i,\tau}}{p^m_{i,\tau}} y_{i,\tau},$$

Plugging this and the producer's production function (5) into the definition of value added yields an industry's value added $y^{va}_{i,\tau}$ as,

$$y^{va}_{i,\tau} = \bar{\alpha}_{m,i} a_{i,\tau} k^{\alpha_{u,i}}_{i,\tau} l^{1-\alpha_{u,i}}_{i,\tau},$$

where the corresponding value added deflator is $p^{va}_{i,\tau} = p_{i,\tau}(p_{i,\tau}/p^m_{i,\tau})^{\alpha_{m,i}/(1-\alpha_{m,i})}$.

In the meanwhile, the production function of the gross output implies,

$$\boldsymbol{g}_{\tau}^{y} = (\boldsymbol{I} - \boldsymbol{\alpha}_{m})\boldsymbol{g}_{\tau}^{va} + \boldsymbol{\alpha}_{m}\boldsymbol{g}_{\tau}^{m}, \tag{9}$$

where $\boldsymbol{I}$ and $\boldsymbol{\alpha}_m$ are a unit matrix and a diagonal matrix of $\alpha_{m,i}$, respectively.

Plugging (7) and (8) into (9) and solving for $\boldsymbol{g}^{y}$ yields the following,

$$\boldsymbol{g}_{\tau}^{y} = \underbrace{\left[\boldsymbol{I} - \boldsymbol{\alpha}_{m}\boldsymbol{\Omega}_{m} - (\boldsymbol{I} - \boldsymbol{\alpha}_{m})\boldsymbol{\alpha}_{u}\boldsymbol{\Omega}_{u}\right]^{-1}(\boldsymbol{I} - \boldsymbol{\alpha}_{m})}_{\equiv\boldsymbol{\Theta}}\boldsymbol{g}_{\tau}^{A}, \tag{10}$$

where $\boldsymbol{\Theta}$ is the generalized Leontief inverse that reflects both production and investment networks. Plugging it into (7) and (8) leads to the following alternative expresson of value added in terms of the exogenous forcing variables,

$$\boldsymbol{g}_{\tau}^{va} = (\boldsymbol{I} + \boldsymbol{\alpha}_{u}\boldsymbol{\Omega}_{u}\boldsymbol{\Theta})\boldsymbol{g}_{\tau}^{A}. \tag{11}$$

Denoting a vector of industries' value-added shares in GDP that is time invariant on the BGP as $\boldsymbol{\omega}_{nv}$, the aggregate GDP growth rate is the weighted sum of industry's value added as follows,

$$g_{\tau}^{va} = \boldsymbol{\omega}_{nv}'(\boldsymbol{I} + \boldsymbol{\alpha}_{u}\boldsymbol{\Omega}_{u}\boldsymbol{\Theta})\boldsymbol{g}_{\tau}^{A}. \tag{12}$$

Consequently, we express the multiplier upon a change in exogenous variable $\boldsymbol{g}^{A}$ as follows,

$$\frac{\partial g_{\tau}^{va}}{\partial \boldsymbol{g}_{\tau}^{A}} = \underbrace{\boldsymbol{\omega}_{nv}}_{\text{Direct effect}} + \underbrace{\boldsymbol{\Theta}'\boldsymbol{\Omega}_{u}'\boldsymbol{\alpha}_{u}'\boldsymbol{\omega}_{nv}}_{\text{Indirect effect}}, \tag{13}$$

The first and second terms reflect the direct and indirect effects of industry's forcing variable g_{τ}^{A} on the aggregate GDP growth rate g_{τ}^{va}. The latter indirect effects emerge through the production and investment networks.

Foerster et al. (2022) stress that the indirect effects arise because of the capital deepening. This is evidence from the fact that the indirect effects disappear when the capital share in production is zero: $\boldsymbol{\alpha}_{u} = \boldsymbol{0}$. Further, the indirect effects from other industries are amplified through production and investment networks. The generalized Leontief inverse $\boldsymbol{\Theta}$ in (10) is the source of the amplification. To understand this point, we rewrite $\boldsymbol{\Theta}$ as follows,

$$\boldsymbol{\Theta} = \left[\boldsymbol{I} + \tilde{\boldsymbol{\Omega}} + \tilde{\boldsymbol{\Omega}}^{2} + \tilde{\boldsymbol{\Omega}}^{3} + ... + \tilde{\boldsymbol{\Omega}}^{\infty}\right](\boldsymbol{I} - \boldsymbol{\alpha}_{m}), \tag{14}$$

where $\tilde{\boldsymbol{\Omega}} \equiv \boldsymbol{\alpha}_{m}\boldsymbol{\Omega}_{m} + (\boldsymbol{I} - \boldsymbol{\alpha}_{m})\boldsymbol{\alpha}_{u}\boldsymbol{\Omega}_{u}$. By definitions of input-output table and capital flow table, all elements of $\tilde{\boldsymbol{\Omega}}$ are greater than zero, and hence, those of $\boldsymbol{\omega}_{nv}'\boldsymbol{\alpha}_{u}\boldsymbol{\Omega}_{u}\boldsymbol{\Theta}$ are also so. Accordingly, the total effect of a change in g_{i}^{A} is always greater than its direct effect. (14) suggests that changes in one industry affect other industries linked by intermediates and investment-goods transactions, and that the impact on that industry spills over further into other industries for multiple times. As argued in Acemoglu et al. (2012), industries located at more "central" positions in the production and investment networks play a more important role in determining the aggregate GDP trend growth rate.

4.3 Empirical analysis

Using the growth accounting framework, we quantitatively examine the impact of industry-specific factors in labor and TFP trend growth rates onto the aggregate GDP trend growth rate. First, we describe the key ingredients of our model, the parameters that govern the production and investment networks. Subsequently, we quantify the industry multipliers derived in the previous section and identify industries exerting substantial influence on the GDP's trend growth rate. Furthermore, we employ historical decomposition to determine which industry-specific factors have explained the trend growth rate of GDP, thereby shedding light on underlying economic dynamics.

4.3.1 Model parameters

We outline the construction of model parameters. In our benchmark economy, the intermediate input-output matrix $\mathbf{\Omega}_m$, intermediate input shares $\boldsymbol{\alpha}_m$, and capital shares $\boldsymbol{\alpha}_u$ are obtained from the 2015 input-output table in the JIP2021 database.[21] As in the section 3.1, the data obtained from JIP2015 and JIP2021 are re-aggregated to match the industry classification of the JIP-HGP database.

The investment input-output matrix $\mathbf{\Omega}_u$ is obtained from the 2015 "Fixed Capital Matrix (private sector)" published by the Ministry of Internal Affairs and Communications. The fixed capital matrix shows the commodity in the columns and the sectors in the rows. Since we are interested in the flow of capital from industry to industry, we match the commodity codes to the sectors and re-aggregate sectors into the 24 industries of the JIP-HGP database, with reference to the Japan Standard Industrial Classification.

Figure 8 shows the investment network for Japan.[22] This figure shows how investment goods from one industry are used in which other industries. The Construction, Service, and General machinery nodes are particularly large, indicating that these are hubs in Japan's investment network. Construction is linked to a wide range of industries, especially Housing, Other (Government), and Real Estate. Service also links to a number of industries, especially the Finance and insurance industry, and according to the fixed capital matrix, most of these links are due to the provision of software. It is not surprising that general machinery has a strong investment network with the manufacturing industry, as other manufacturing industries use

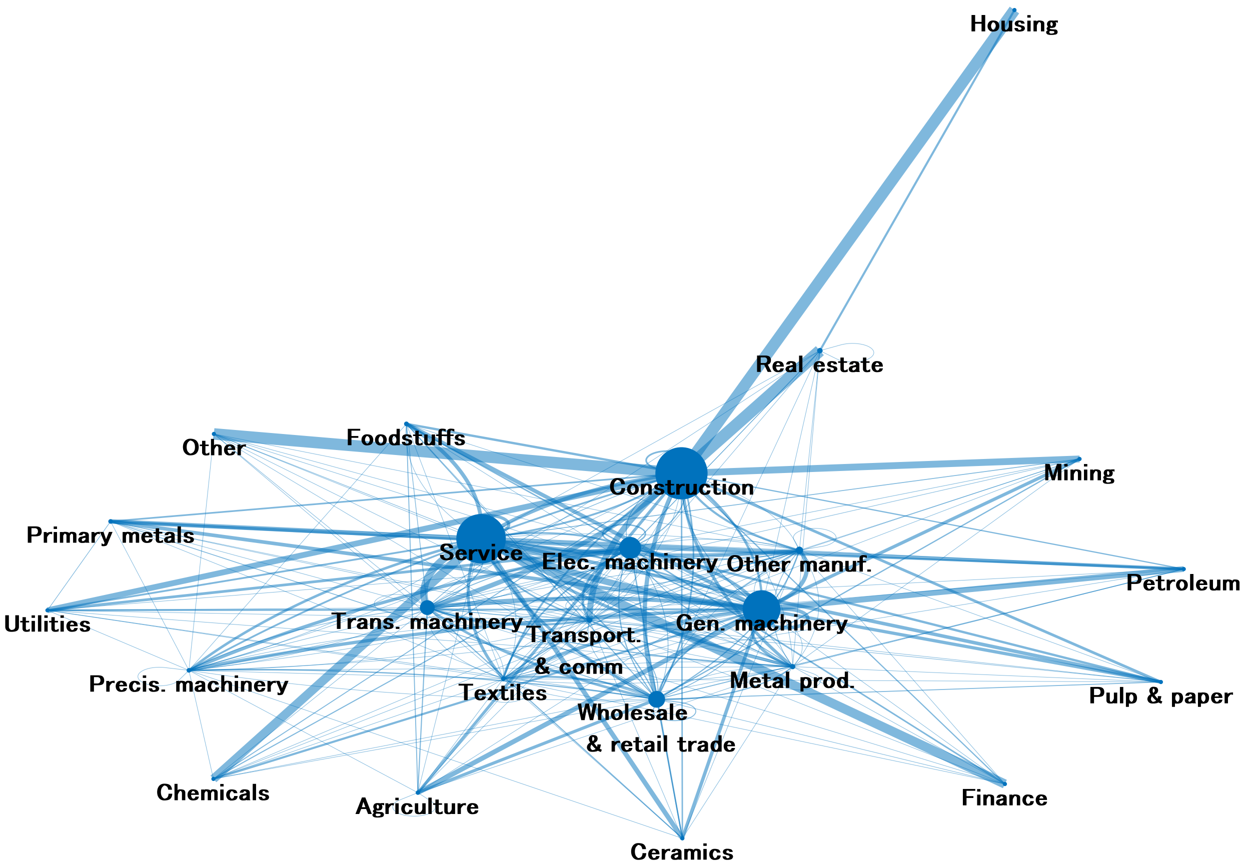
[21] Among the values of the real input-output table in the JIP database, some are published as negative values. We replace them with zero for aggregation.

[22] Here, we present only the investment network because the figure of production network is less informative: it does not exhibit the clear core-periphery structure as the figure of investment network does.

much of the investment goods produced in General machinery. We can find the similar pattern in networks of intermediates.

The rise and fall of these "hub" industries can, of course, have a significant impact on other industries. For example, innovations in the software industry will have a positive impact on the productivity of other industries that use it. In the next and subsequent sections, we analyze the Japan's economy in light of such network structures.

Figure 8: Investment network



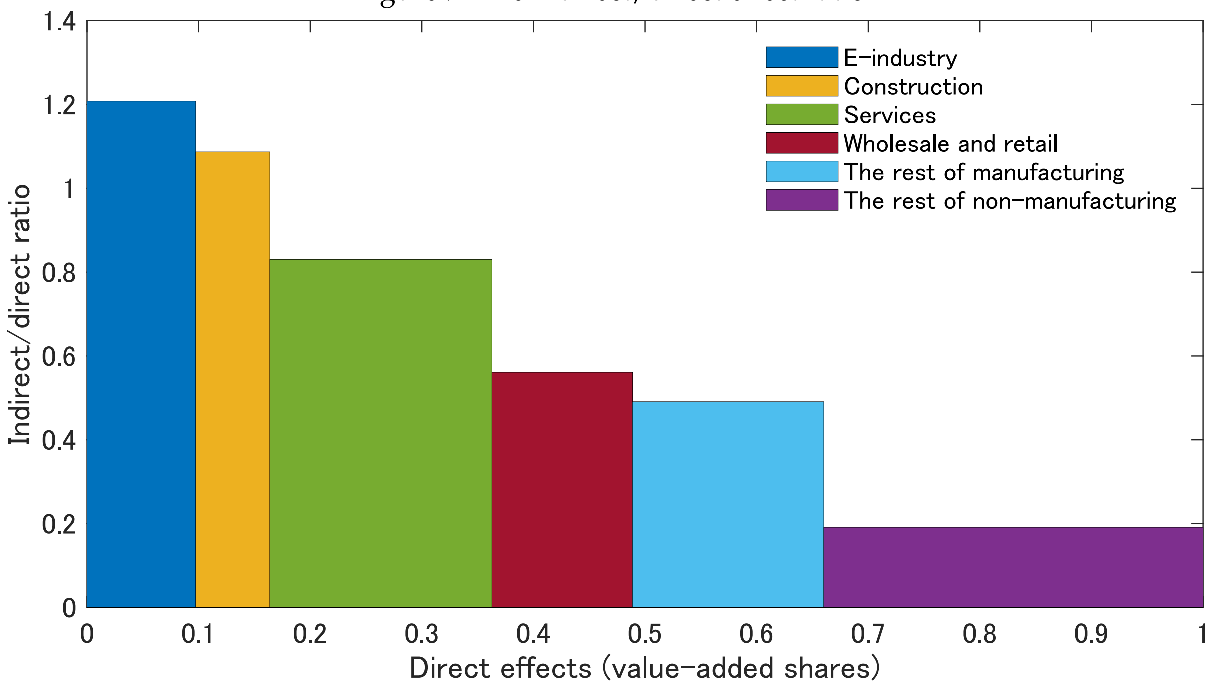
Note: This figure illustrates the investment network: circle and lines represent industries and capital flows, respectively. The size of a circle indicates the sales share in investment markets. The width of lines represents the relative size of bidirectional capital flows.

Conditional on these parameters, we obtain aggregate GDP growth along the BGP from (12). Section 4.5 examines the sensitivity of results to alternative parameter values.

4.3.2 Multipliers

Table 4 reports the direct and indirect effects of an industry's exogenous variations on the aggregate GDP trend growth rate. The direct effect of a given industry is its value-added share. The indirect effect of an industry is the indirect impact of its exogenous variations on the aggregate level through production and investment networks. According to Table 4, industries with high direct effects include the Equipment industry (0.10, hereafter E-industry), which is the sum of the machinery industries,[23] Construction (0.07), Services (0.20), Wholesale & Retail Trade (0.13), and Transportation & Communication (0.07). The former three industries (E-industry, Construction, and Services) differ significantly from the latter two (Wholesale & Retail Trade and Transportation & Communication) in the size of their indirect effects. Specifically, the indirect effects of the former three industries (0.12, 0.07, and 0.17) are similar to or larger than their direct effects (0.10, 0.07, and 0.20), as these industries are located at the nodes of production and investment networks by providing intermediate inputs and investment goods to various other industries. In contrast, the indirect effects of the latter two industries (0.07 and 0.02) are smaller than their direct effects (0.13 and 0.07), as these industries are located at the periphery of the production and investment networks.

Figure 9: The indirect/direct effect ratio



Note: The indirect/direct ratio refers to the ratio of indirect effects relative to direct effects in (13). "E-industry" is General machinery + Electrical machinery + Transportation machinery + Precision machinery; "The rest of manufacturing" is Foodstuffs + Textile+ Pulp and paper + Chemicals + Petroleum and coal products + Ceramics, soil, and stone products + Other manufacturing; "The rest of non-manufacturing" is Agriculture, forestry and fisheries + Mining + Electricity, gas and water supply + Finance and insurance + Real estate + Transportation and communication + Other + Housing.

Figure 9 demonstrates the pronounced spillover effects in the E-industry, construction, and service sectors, showing the ratio of indirect to direct effects. For simplicity, some industries are grouped together. The value-added share is represented along the horizontal axis, where industries with larger spillover effects are depicted with taller bars, and those with smaller effects with wider bars. The figure distinctly highlights that investment-related industries like the E-industry, construction, and service exhibit notable spillover effects. Conversely, the

[23] Greenwood et al. (1997) consider this E-industry as a source of investment-specific technological progress.

Table 4: Industry multipliers

Industry	Direct effects	Indirect effects	Total effects
1. Agriculture, forestry & fisheries	0.04	0.00	0.04
2. Mining	0.00	0.01	0.01
3. Foodstuffs	0.04	0.01	0.04
4. Textiles	0.01	0.00	0.02
5. Pulp & paper	0.01	0.00	0.01
6. Chemicals	0.02	0.01	0.04
7. Petroleum & coal products	0.01	0.00	0.02
8. Ceramics, soil, & stone products	0.01	0.01	0.02
9. Primary metals	0.02	0.02	0.05
10. Metal products	0.01	0.01	0.02
11. General machinery	0.03	0.05	0.08
12. Electrical machinery	0.04	0.04	0.08
13. Transportation machinery	0.03	0.02	0.05
14. Precision machinery	0.01	0.00	0.01
15. Other manufacturing	0.03	0.02	0.05
16. Construction	0.07	0.07	0.14
17. Utilities	0.03	0.01	0.04
18. Wholesale & retail trade	0.13	0.07	0.20
19. Finance & insurance	0.05	0.01	0.06
20. Real estate	0.04	0.01	0.05
21. Transportation & communication	0.07	0.02	0.10
22. Service	0.20	0.17	0.36
23. Other	0.04	0.00	0.04
24. Housing	0.06	0.00	0.06
Equipment industry (11+12+13+14)	0.10	0.12	0.22
Equipment industry + construction	0.16	0.19	0.35
Overall	1.00	0.58	1.58

Note: Equipment industry is the sum of general machinery, electrical machinery, transportation machinery, and precision machinery. See (13) for direct and indirect effects.

wholesale & retail, the rest of manufacturing, and other non-manufacturing sectors display comparatively lesser spillover effects.

Another interesting point revealed in Table 4 is heterogeneity in the degree of spillovers, which will lead to the composition effects. For example, suppose that TFP rises in industries with large spillovers through indirect effects, while TFP declines by the same amount in industries with small indirect effects. According to Hulten (1978), if the value-added shares of the two are the same, the change in aggregated TFP would be zero. Nevertheless, GDP would rise through indirect effects. The existence of these composition effects calls for a structural approach using a multi-industry model.

4.3.3 Historical decomposition of trend growth rates

This section presents a historical decomposition of the aggregate GDP growth into the contribution of common and industry-specific factors. To this end, we combine the trend growth rates in industries' TFP and labor in Section 3 with the growth accounting equation (12) and the multipliers in Table 4. It is noted that we omit the transition dynamics around the BGP because the low-frequency growth trends are of interest.

The following outlines the specific procedure. The factor model of (3) allows us to decompose the trend growth rates of labor input and TFP for each industry into common factors, $(\lambda_i^l f_\tau^l, \lambda_i^a f_\tau^a)$, and industry-specific factors, $(\epsilon_{i,\tau}^l, \epsilon_{i,\tau}^a)$. Then, using the growth accounting equation presented in (11), we can express the vector of the trend growth rates of industries' value added as follows,

$$\boldsymbol{g}_\tau^{\boldsymbol{va}} = (\boldsymbol{I} + \boldsymbol{\alpha}_u \boldsymbol{\Omega}_u \boldsymbol{\Theta}) \left[\boldsymbol{\lambda}^a f_\tau^a + \boldsymbol{\epsilon}_\tau^{\boldsymbol{a}} + (\boldsymbol{I} - \boldsymbol{\alpha}_u) \left(\boldsymbol{\lambda}^l f_\tau^l + \boldsymbol{\epsilon}_\tau^{\boldsymbol{l}} \right) \right]. \tag{15}$$

where $\boldsymbol{g}_\tau^{\boldsymbol{va}}$ is the vector of the industry's trend growth rates, $\boldsymbol{\lambda_l}$ and $\boldsymbol{\lambda_a}$ are the vectors of factor loadings estimated in (3), and $\boldsymbol{\epsilon}_\tau^{\boldsymbol{l}}$ and $\boldsymbol{\epsilon}_\tau^{\boldsymbol{a}}$ are the vectors of industry specific factors estimated in (3). As in (12), the GDP trend growth rate is denoted as

$$g_\tau^{va} = \boldsymbol{\omega}_{\boldsymbol{nv}}' \boldsymbol{g}_\tau^{\boldsymbol{va}}, \tag{16}$$

Consequently, by combining (15) and (16), we can calculate the contributions of direct and indirect effects as in (13),

$$\begin{aligned} g_\tau^{va} = & \underbrace{\boldsymbol{\omega}_{\boldsymbol{nv}}' \left[\boldsymbol{\lambda}^a f_\tau^a + \boldsymbol{\epsilon}_\tau^{\boldsymbol{a}} + (\boldsymbol{I} - \boldsymbol{\alpha}_u) \left(\boldsymbol{\lambda}^l f_\tau^l + \boldsymbol{\epsilon}_\tau^{\boldsymbol{l}} \right) \right]}_{\text{Contribution through direct effect}} \\ & + \underbrace{\boldsymbol{\omega}_{\boldsymbol{nv}}' \boldsymbol{\alpha}_u \boldsymbol{\Omega}_u \boldsymbol{\Theta} \left[\boldsymbol{\lambda}^a f_\tau^a + \boldsymbol{\epsilon}_\tau^{\boldsymbol{a}} + (\boldsymbol{I} - \boldsymbol{\alpha}_u) \left(\boldsymbol{\lambda}^l f_\tau^l + \boldsymbol{\epsilon}_\tau^{\boldsymbol{l}} \right) \right]}_{\text{Contribution through indirect effect}}. \end{aligned}$$

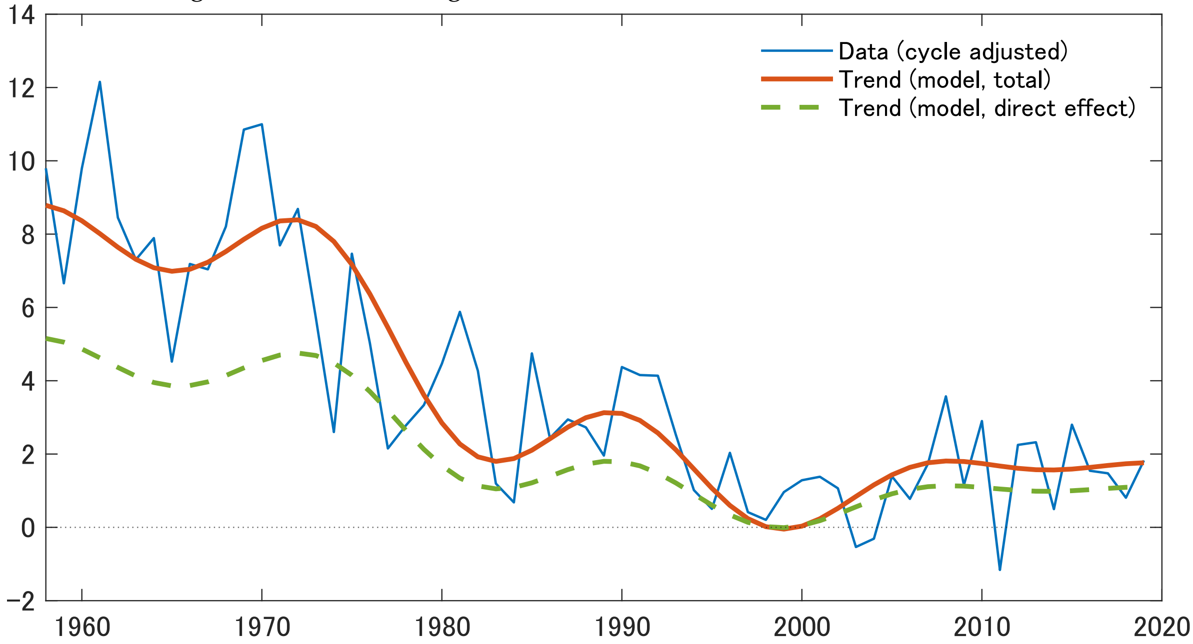
Figure 10 illustrates the model-implied trend GDP growth rates.[24] The difference between the red line and green dotted line corresponds to the model-implied indirect effects. It is interesting that the direct effect alone cannot explain the low-frequency trend of the aggregate GDP. It is consistently low relative to the actual data. The contribution of indirect effects was large during the high-growth period from the 1950s to the early 1970s, with indirect effects contributing 3 percentage points out of an annual growth rate of about 8 percent. After the late 1970s, the contribution of the indirect effect has shrunk to approximately 1 percent. This figure underlines the necessity to take the network multiplier effects into consideration.

Next, we perform the historical decomposition of the trend GDP growth rate into the contributions of common and industry-specific factors. These contributions include not only the direct effects but also the indirect effects through the production and investment networks. Therefore, this historical decomposition depicts the root cause of the long-term economic growth through the lens of industry.

To begin with, Figure 11 presents the model implied trend growth rate of GDP together

[24] Note that our model does not consider transition dynamics.

Figure 10: GDP trend growth rate: direct effects alone vs total effects



Note: Red and green dotted lines are the model implied trend GDP growth rates with total effects and that with direct effects alone, respectively. See (13) for total and direct effects.

with the contribution of common factor and industry-specific factors, separately. This figure illustrates that the major development in the trend growth rate is attributable to the movements of the common factor. In contrast, the industry-specific factors account for medium-term fluctuations around the common factors.

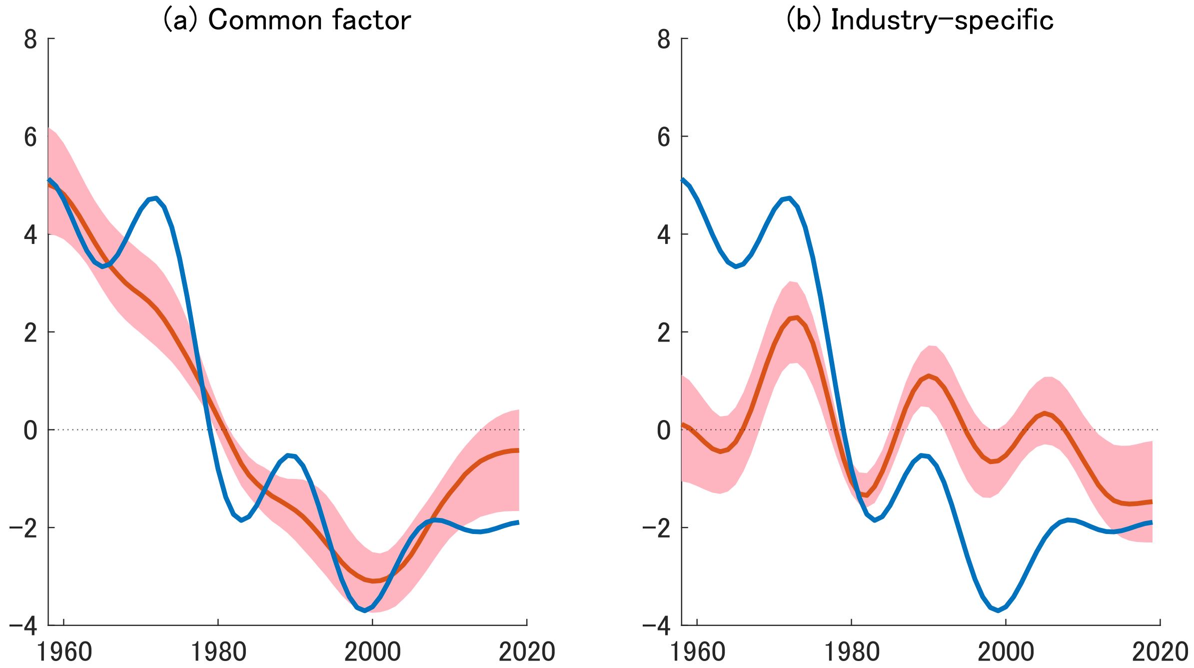
Next, Figure 12 presents historical decomposition in detail. The model suggests that the secular declining trend from the 1950s to the 1990s is mainly attributable to the TFP common factors. The finding is in line with Hayashi and Prescott (2002). The negative contribution of the common labor factor in the 1990s reflects the working-hour reducing policy implemented during this period. One interesting point is that even though common TFP factors contributed to increase the trend GDP growth over the last two decades,[25] the E-industry specific factor contributed to push it down. Consequently, the trend GDP growth rate remained almost flat. While lower potential growth was a policy issue over the last two decades, this result suggests that it is important to consider industry-specific factors.

4.4 Comparison with US

This subsection discusses the comparison with US results. In the context of Japan, we find that common factors considerably impact the GDP growth rate, with industry-specific factors playing a supportive role. This pattern may be unique to Japan's economy. In contrast, findings from the US present a different scenario. According to Foerster et al. (2022), in the US, the

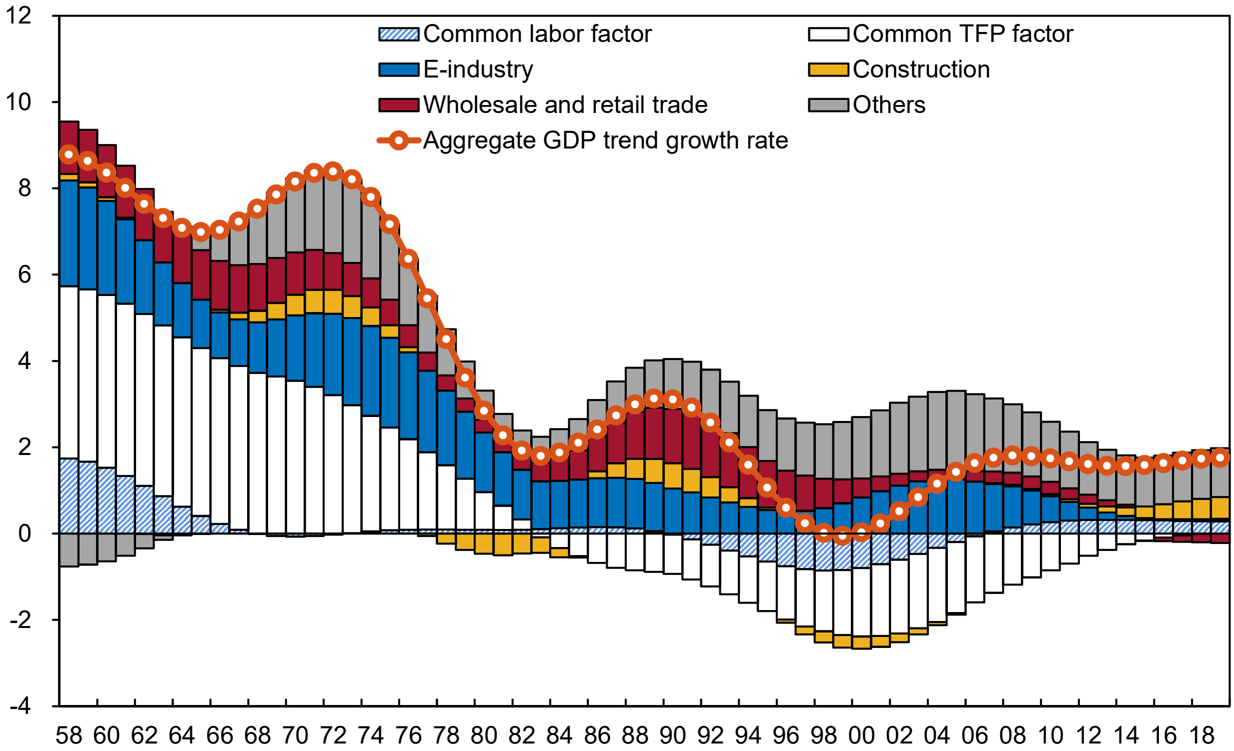
[25] Fueki and Kawamoto (2009) argue that the information technology had served as a general purpose technology in the post 2000.

Figure 11: Contribution of common and industry-specific factors



Note: Blue lines are the model implied trend growth rate of GDP and red lines are the contribution of common and industry-specific factors. The shaded area represents the 68% credible intervals. All figures are demeaned.

Figure 12: What is the major source of the aggregate GDP trend growth rate



Note: The historical mean of each series is allocated to the contributions of common and industry-specific factors based on the posterior median of R^2 that corresponds to the fraction of the variance in the trend GDP growth rate attributed to the common factor.

industry-specific factors is dominant, while the common factors play a supportive role. This difference underscores the unique economic dynamics at play in each market, suggesting that factors influencing GDP growth can vary significantly between countries.

The decomposition of the US data, as shown in Figure 13, clearly demonstrates this difference.[26][27] Additionally, Figure 14 reveals a striking contrast: in Japan, the explanatory power of the common factor exceeds 60%, whereas in the US, it is around 20%.[28] The observed differences between Japan and the US reflect variations in industrial dynamism. In the US, the economic growth has been sustained through the rise and fall of industries, underpinned by a flexible labor market and the active entry and exit of firms. Indeed, the contribution of entry and exit effects to economic growth is significant (Baily et al. (1992), Foster et al. (2001), Hogen et al. (2017), Yagi et al. (2022)). In contrast, Japan's labor market is more rigid, exemplified by stringent dismissal legislation, and the country experiences less frequent entry and exit of firms. In fact, it has been noted that the primary source of economic growth in Japan lies in productivity improvements within firms, and the effects of entry and exit are relatively small. (Fukao et al. (2006), Griffin and Odaki (2009), Hogen et al. (2017), Nakamura et al. (2019), Yagi et al. (2022)). These differences could potentially explain the disparities observed in the estimation results.

Nevertheless, there are notable similarities between the two countries. A key similarity is the long-term decline in growth rates over the past two decades. In the US, similar to Japan, the equipment-related industry (termed 'E-industry' in Japan and 'durable goods industry' in the US) has significantly contributed to the slowdown in GDP growth over this period.[29] This parallel trend is in line with the global decline in research productivity, as discussed in Bloom et al. (2020). Further, our findings support Takahashi and Takayama (2022b)'s conclusion that the global secular low growth is attributable to the equipment-specific technological stagnation.

4.5 Robustness checks

This subsection runs robustness exercises for assumptions in the benchmark economy.

First, this study examines the sensitivity of estimated factors to the prior for the factor loadings, η. In Section 3.2.2, η is set to 1.0. Figure 15 summarizes the cases where this assumption

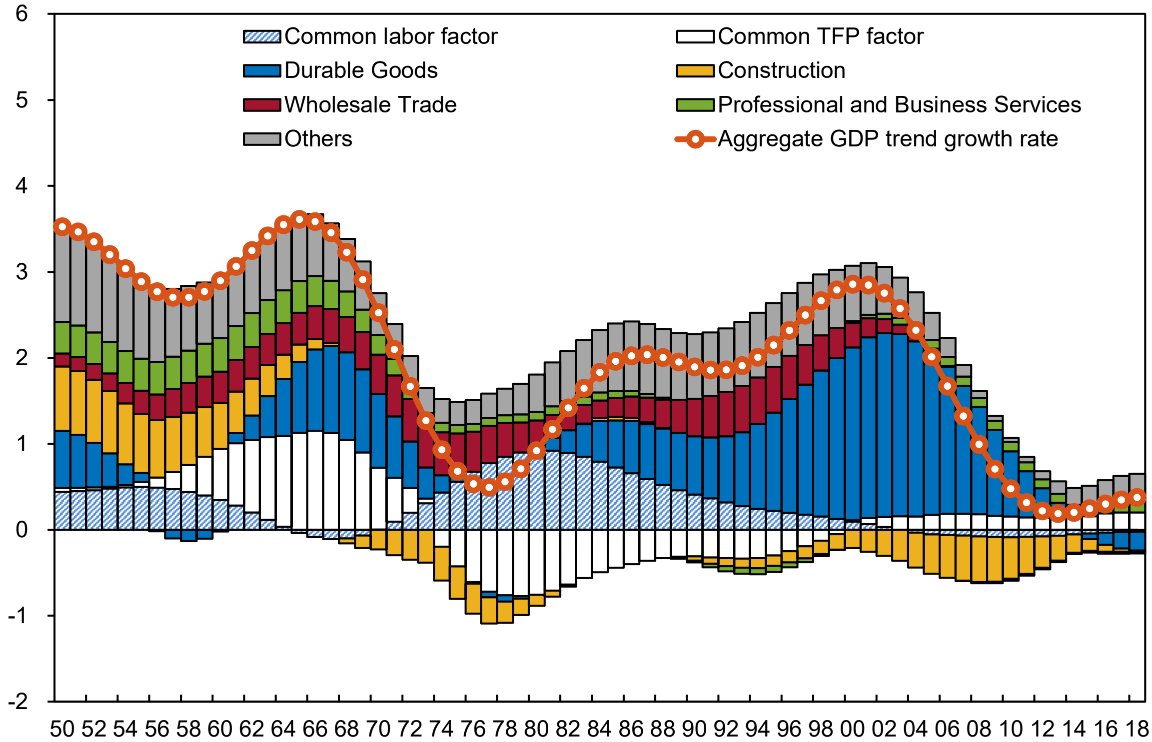
[26] We re-estimate the model of Foerster et al. (2022) basically based on their replication package. However, to align with our exercise in Japan, we transform the data into per working-age population basis, re-estimate the model, and calculate the decomposition in Figure 13 to make comparison with our results. See also Appendix D for details.

[27] Comparing with Figure 12, we observe that the trend GDP growth rate in the US has been lower than that of Japan over the past decade. Fernández-Villaverde et al. (2023) note that this reversal in the growth rates between Japan and the US occurs when using the GDP growth rate per working-age population.

[28] In the original result of Foerster et al. (2022), the explanatory power of the common factor is around one-fourth in the US. Our exercise slightly differs from this original results as we re-estimate using data converted to a per working-age-population basis.

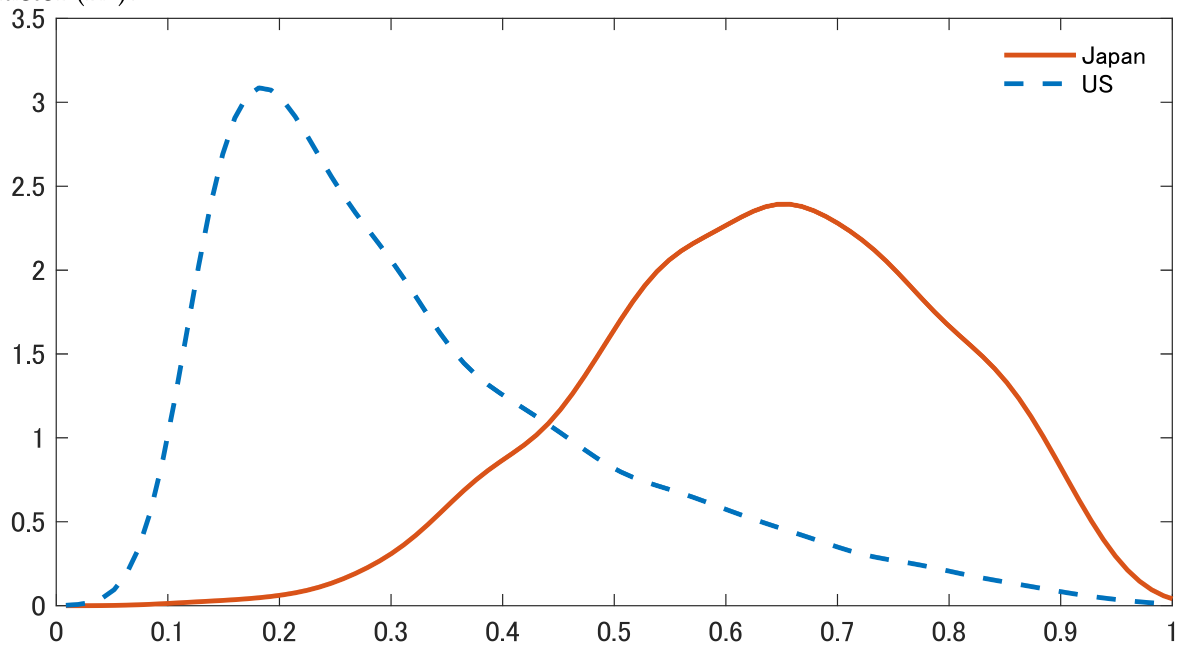
[29] In the US, the prominence of 'superstar firms' is reportedly on the rise. While the market value of these companies in the stock market is indeed substantial, their relative contribution to the value-added growth remains comparatively small. Consequently, although the contribution of industries, such as the professional business services (PBS) industry and Information industry, has been increasing in recent years, it has not been sufficient to counteract the downward pressure exerted by the durable goods industry.

Figure 13: What is the major source of the aggregate GDP trend growth rate in US



Note: The historical mean of each series is allocated to the contributions of common and industry-specific factors based on the R^2 values .

Figure 14: To what extent variations in the GDP trend growth is attributable to the common factor (R^2)?



Note: Posterior distributions for the fraction of the variance in the trend GDP growth rate attributed to the common factor.

is changed. The top row shows the benchmark economy, and the second and the third rows show the cases where η is changed to 0.5, 2.0, respectively. For each row, the left panel shows the model-implied trend GDP growth rate and its decomposition, and the right panel plots the posterior density for R^2, the fraction of the variance in trend GDP growth explained by the common factors. The median estimates of R^2 in each case are 0.64, 0,71 and 0.49, respectively, clearly indicating that the common factor has played a major role in GDP growth. We thus conclude that the finding that common factor is the main driver of trend GDP growth is robust to changes in the priors for the factor loadings.

Next, we perform a robustness check with parameters of the structural model. The specification of this study is simplistic: the production function and the goods aggregators take a Cobb-Douglas form, which implies the constant input share for production function and the constant expenditure share for aggregator function. Based on this assumption, in the benchmark model, the parameters of input-output table and the fixed capital matrix are those of 2015, and the expenditure share is fixed to the mean of sample periods. However, when using specifications other than the Cobb-Douglas type, input shares and expenditure shares are not necessarily constant.

To examine whether the Cobb-Douglas assumption is too simplistic or not, we check the robustness of results with respect to time-varying parameters, instead of the fixed parameters. Figure 16 shows the case where those parameters are changing in each year after 1995.[30] It presents the robustness of our results with respect to the model parameters. The GDP trend growth rate moves along with that in the benchmark model: the mean of differences is small and only 0.13 percentage points. Therefore, our assumption with respect to the function form is not overly simplistic.

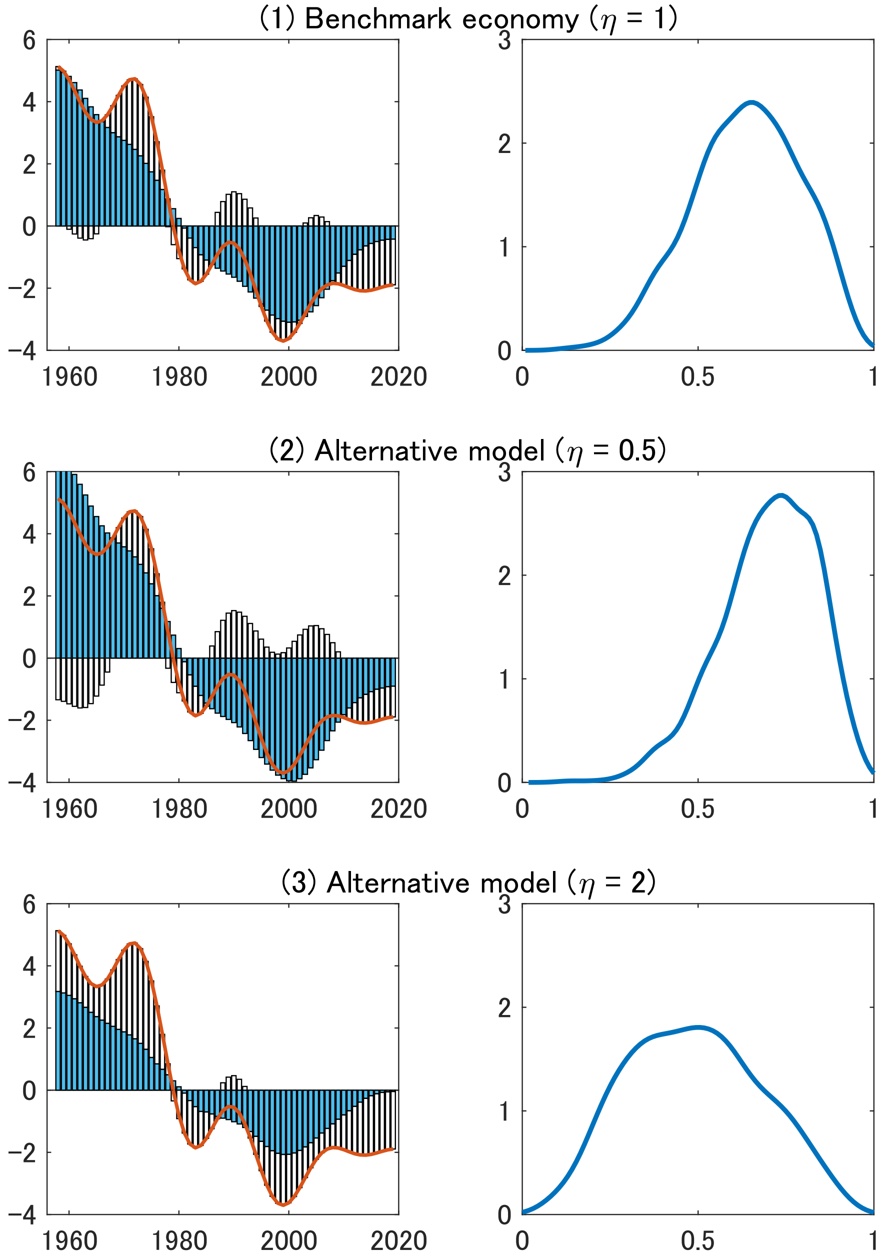
Finally, we conducted a robustness check against changes in the import-penetration ratio. Typically, a portion of intermediate inputs consists of imported goods; however, the JIP input-output tables do not differentiate between imported and domestic goods. Therefore, our results may overestimate the spillover effects from industries to industries. To address this issue, we compile an input-output matrix exclusively for domestic goods by excluding imported goods from the input-output table,[31] and then we assessed how the benchmark results would change accordingly. The findings, presented in Figure 17, indicate that the impact remains relatively minor, even when excluding imported goods from the input-output table. Specifically, the average reduction in GDP growth rate is 0.41 percentage points. Thus, even considering the increased import penetration ratio, its effect is not significantly substantial.[32]

[30]Due to the data limitations, We pick 1995 as a starting point of this exercise.

[31]The Ministry of Internal Affairs and Communications provides an import table that extracts only the imports of intermediate inputs, and by subtracting this table from our input-output table, we obtain an alternative input-output table that represents only domestic intermediate input networks.

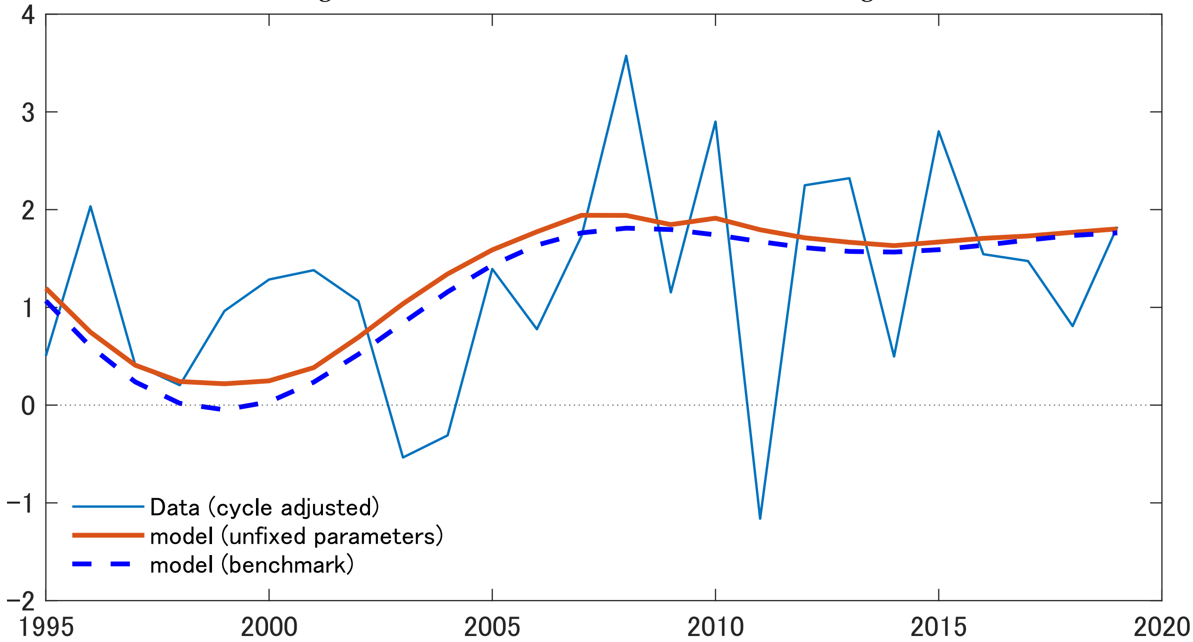
[32]It is worth noting that the result of this alternative case underestimates the spillover effect in the past when the import penetration ratio was lower, because, for this exercise, we use the input-output matrix of 2015 when the import penetration ratio have considerably increased.

Figure 15: Robustness check for different parameter values



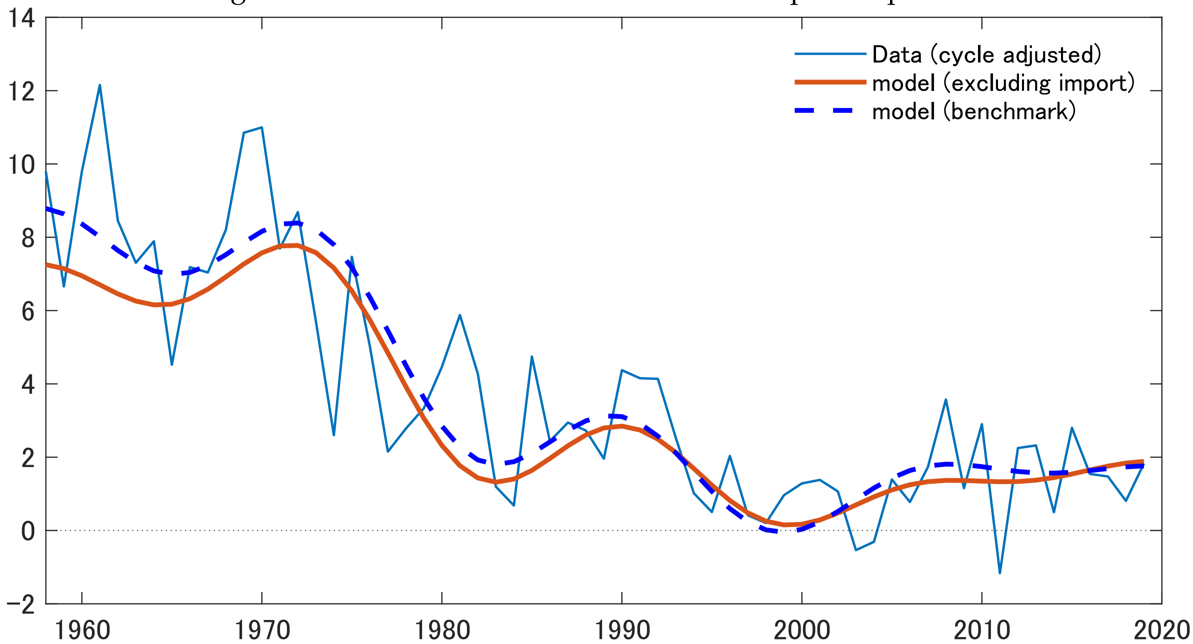
Note: Robustness to changes in statistical model. Each vertical panel of the figure shows results for a different specification of the prior, η. The left vertical panel of the figure shows the model-implied trend GDP growth rate (red line, deviation from average) and its decomposition into changes due to the common factor (blue bars) and industry-specific factor (white bars). The right vertical panel of the figure shows the posterior distribution for the fraction of the variance in trend GDP growth attributed to the common factor.

Figure 16: Robustness check for unfixed weights



Note: The solid red line shows the GDP growth rate of the case where the input-output table, the fixed capital matrix, and the nominal value-added share are variable since 1995. The fixed capital matrix is linearly interpolated from 1995, 2000, 2005, 2011, and 2015 (since the fixed capital matrix is not published by the Ministry of Internal Affairs and Communications, the fixed capital matrix from the JIP database is used for 1995 and 2000). Since the latest JIP input-output table, JIP2021, publishes values up to 2018, 2018 values are used for 2019 values. The blue dotted line is the specification with parameters fixed to 2015, which is the same as the solid red line in Figure 10.

Figure 17: Robustness check for alternative input-output table



Note: The solid red line is the GDP growth rate calculated using the input-output table, which excludes the impact of imports from intermediate inputs by drawing an import table. The value-added share vector for aggregation is the share of the long-term average of nominal value-added minus the 2015 import table. The blue dotted line is the GDP growth rate of benchmark economy, which is the same as the solid red line in Figure 10.

5 Concluding remarks

Employing the methodology of Foerster et al. (2022), this study examines to what extent the Japan's long-term GDP growth rate is attributable to the industry-specific factors. Using industry data in 1958-2019, the empirical assessment reveals that the industry-specific factors account for the one-third of long-run GDP rate growth. This result contrasts with that in the US: Foerster et al. (2022) finds the industry-specific factors account for three-fourth of US long-run growth. Although the explanatory power of industry-specific factors is relatively low in Japan, this does not necessarily mean they are unimportant. Since the 2000s, when the natural rate of interest declined and monetary policy operation faced the constraints of zero interest rates, industry-specific factors, particularly the E-industry factor, have contributed to depressing the long-term economic growth rate.

The results of this study serve as a guide for future research directions. Utilizing a statistical model, this study successfully describes the long-term developments of the GDP growth rate. However, it does not elucidate the reasons why the explanatory power of industry-specific factors varies from country to country. Further, while we conducted a comparative analysis between Japan and the US, comparisons with other advanced economies and emerging countries are interesting topics. Pursuing research in these directions could be a promising avenue for future studies.

References

Acemoglu, Daron, Vasco M. Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, "The Network Origins of Aggregate Fluctuations," *Econometrica*, September 2012, *80* (5), 1977–2016.

Ahearne, Alan and Naoki Shinada, "Zombie Firms and Economic Stagnation in Japan," *International Economics and Economic Policy*, December 2005, *2* (4), 363–381.

Baily, Martin Neil, Charles Hulten, David Campbell, Timothy Bresnahan, and Richard E. Caves, "Productivity Dynamics in Manufacturing Plants," *Brookings Papers: Microeconomics*, 1992, *4*, 187–267.

Bloom, Nicholas, Charles I. Jones, John Van Reenen, and Michael Webb, "Are Ideas Getting Harder to Find?," *American Economic Review*, 2020, *110* (4), 1104–1144.

Braun, R Anton and Etsuro Shioji, "Investment Specific Technological Changes in Japan," *Seoul Journal of Economics*, 2007, *20* (1), 165–200.

Carvalho, Vasco M, Makoto Nirei, Yukiko U Saito, and Alireza Tahbaz-Salehi, "Supply Chain Disruptions: Evidence from the Great East Japan Earthquake," *The Quarterly Journal of Economics*, 2021, *136* (2), 1255–1321.

Fernald, John G., Robert E. Hall, James H. Stock, and Mark W. Watson, "The Disappointing Recovery of Output after 2009," *Brookings Papers on Economic Activity*, 2017, *Activity 48 (Spring)*, 1–81.

Fernández-Villaverde, Jesús, Gustavo Ventura, and Wen Yao, "The Wealth of Working Nations," NBER working paper, National Bureau of Economic Research November 2023.

Foerster, Andrew T., Andreas Hornstein, Pierre-Daniel G. Sarte, and Mark W. Watson, "Aggregate Implications of Changing Sectoral Trends," *Journal of Political Economy*, 2022, *130* (12), 3286–3333.

Foster, Lucia, John C. Haltiwanger, and C. J. Krizan, "Aggregate Productivity Growth: Lessons from Microeconomic Evidence," NBER Chapters, in: New Developments in Productivity Analysis January 2001.

Fueki, Takuji and Takuji Kawamoto, "Does Information Technology Raise Japan's Productivity?," *Japan and World Economy*, 2009, *21*, 325–336.

__ , Ichiro Fukunaga, Hibiki Ichiue, and Toyoichiro Shirota, "Measuring Potential Growth with an Estimated DSGE Model of Japan's Economy," *International Journal of Central Banking*, March 2016, *12* (1), 1–32.

Fukao, Kyoji, *The Structural Causes of Japan's "Two Lost Decades": Forging a New Growth Strategy (Ushinawareta 20nen to nihonkeizai: kozotekigenin to saisei heno gendoryoku no kaimei)*, Nikkei Publishing Inc, 2012.

__ , "What is Needed to Improve Japan's Potential Growth Rate? An Analysis Using the JIP Database 2023 (Nihon no senzaiseichoritsu kojo ni nani ga hitsuyo ka? JIP Database 2023 wo tsukatta bunseki)," RIETI Policy Discussion Paper Series 23-P-028, Research Institute of Economy, Trade and Industry (RIETI) November 2023.

__ **and Hyeog Ug Kwon**, "Why Did Japan's TFP Growth Slow Down in the Lost Decade? An Empirical Analysis Based on Firm-Level Data of Manufacturing Firms," *The Japanese Economic Review*, June 2006, *57* (2), 195–228.

__ **and Tatsuji Makino**, "Sources of Labor Productivity Growth in Service Industries: an Industry-level Empirical Analysis Using the JIP Database, 1955-2015 (Service sangyo ni okeru roudou seisansei josyo no gensen: JIP Database wo mochiita sangyo level no jissyo bunseki, 1955-2015)," RIETI Paper Series 21-J-018, Research Institute of Economy, Trade and Industry (RIETI) March 2021.

__ **and Tsutomu Miyagawa, eds**, *Productivity and Japan's Economic Growth; Industry and Firm-Level Empirical Analysis Using the JIP Database (Seisansei to nihon no keizaiseicho; JIP Database ni yoru sangyo, kigyo level no jissho bunseki)*, University of Tokyo Press, 2008.

__ , ed., *Service Sector Productivity and the Japanese Economy: An Empirical Analysis Using the JIP Database (Service sangyo no seisansei to nihon keizai: JIP Database niyoru jissho bunseki to teigen)*, University of Tokyo Press, 2021.

__ , Sumio Hamagata, Tomohiko Inui, Keiko Ito, Hyeog-Ug Kwon, Tatsuji Makino, Tsutomu Miyagawa, Yasuo Nakanishi, and Joji Tokui, "Estimation Procedures and TFP Analysis of the JIP Database 2006 Provisional Version," Discussion papers 07-E-003, Research Institute of Economy, Trade and Industry (RIETI) January 2007.

__ , Young Gak Kim, and Hyeog Ug Kwon, "Plant Turnover and TFP Dynamics in Japanese Manufacturing," Hi-Stat Discussion Paper Series d06-180, Institute of Economic Research, Hitotsubashi University August 2006.

— , **YoungGak Kim, and Hyeog Ug Kwon**, "The Causes of Japan's Economic Slowdown and Necessary Policies: An Analysis Based on the Japan Industrial Productivity Database 2018," *International Productivity Monitor*, 2021, *40*, 56–88.

— , — , — , **and Kenta Ikeuchi**, "Business Dynamism and Productivity Growth under Abenomics: An Empirical Analysis Based on Micro Data from Japan's Economic Census for Business Activity (Japanese)," Discussion Papers (Japanese) 21-J-015, Research Institute of Economy, Trade and Industry (RIETI) March 2021.

Greenwood, Jeremy, Zvi Hercowitz, and Per Krusell, "Long-Run Implications of Investment-Specific Technological Change," *American Economic Review*, 1997, *87*, 342–362.

Griffin, Naomi N. and Kazuhiro Odaki, "Reallocation and Productivity Growth in Japan: Revisiting the Lost Decade of 1990s," *Journal of Productivity Analysis*, 2009, *31* (2), 125–136.

Hayashi, Fumio and E.C. Prescott, "The 1990s in Japan: A Lost Decade," *Review of Economic Dynamics*, 2002, *5* (1), 206–235.

— , **ed.**, *The Causes and Institutions of Economic Stagnation (Keizaiteitai no genin to seido)* number I. In 'Empirical Analysis and Design of Economic Systems (Keizaiseido no jisshoubunseki to sekkei).', Keiso Shobo, 2007.

Hirakata, Naohisa and Yasutaka Koike, "The Labor Share, Capital-Labor Substitution, and Factor Augmenting Technologies," Bank of Japan Working Paper Series 18-E-20, Bank of Japan November 2018.

Hirose, Yasuo and Takushi Kurozumi, "Do Investment-Specific Technological Changes Matter for Business Fluctuations? Evidence from Japan," *Pacific Economic Review*, 2012, *17* (2), 208–230.

Hogen, Yoshihiko, Ko Miura, and Koji Takahashi, "Large Firm Dynamics and Secular Stagnation: Evidence from Japan and the U.S.," Bank of Japan Working Paper Series 17-E-8, Bank of Japan June 2017.

Hosono, Kaoru and Miho Takizawa, "Japan's Productivity Stagnation: Using Dynamic Hsieh-Klenow Decomposition," *Contemporary Economic Policy*, 2022, *40* (1), 218–232.

Hulten, Charles R., "Growth Accounting with Intermediate Inputs," *Review of Economic Studies*, 1978, *45* (3), 511–518.

Ikeuchi, Kenta, Young Gak Kim, Hyeog Ug Kwon, and Kyoji Fukao, "Productivity Dynamics among Japanese Small and Medium-Sized Enterprises–Empirical Analysis Based on the Credit Risk-Database Productivity–(Japanese)," *The Economic Review (Japanese)*, 2018, *69* (4), 363–377.

Inui, Tomohiko, Y.G. Kim, H.U. Kwon, and K. Fukao, "Productivity Dynamics and Japan's Economic Growth (Seisansei dogaku to nihon no keizai seicho)," *The Economic Review (Japanese)*, 2015, *66* (4), 289–300.

Ito, Keiko and Sébastien Lechevalier, "The Evolution of the Productivity Dispersion of Firms: A Reevaluation of Its Determinants in the Case of Japan," *Review of World Economics*, 2009, *145*, 405–429.

Ito, Yojiro and Daisuke Miyakawa, "Performance of Exiting Firms in Japan: An Empirical Analysis Using Exit Mode Data," IMES Discussion Paper Series 22-E-07, Institute for Monetary and Economic Studies, Bank of Japan May 2022.

Jorgenson, Dale W. and Kazuyuki Motohashi, "Information Technology and the Japanese Economy," *Journal of the Japanese and International Economies*, 2005, *19(4)*, 460–481.

— , **Koji Nomura, and Jon D. Samuels**, "A Half Century of Trans-Pacific Competition: Price Level Indices and Productivity Gaps for Japanese and U.S. Industries, 1955-2012," RIETI Discussion Paper Series 15-E-054, Research Institute of Economy, Trade and Industry (RIETI) May 2015.

Katagiri, Mitsuru, "Unleashing Innovation and Entrepreneurship: Ripple Effects of Employment Protection Reforms," RIETI Discussion Paper Series 24-E-022, Research Institute of Economy, Trade and Industry (RIETI) Feb 2024.

Kawakami, Atsushi and Tsutomu Miyagawa, "Product Switching and Firm Performance in Japan," RIETI Discussion Paper Series 10-E-043, Research Institute of Economy, Trade and Industry (RIETI) Sep 2010.

Kawamoto, Takuji, "What Do the Purified Solow Residuals Tell Us about Japan's Lost Decade?," *Monetary and Economic Studies*, 2005, *23(1)*, 113–148.

Kim, YoungGak, Kyoji Fukao, and Tatsuji Makino, "Structural Factors of the "Lost 20 Years" (Japanese)," *The Economic Review (Japanese)*, 2010, *61* (3), 237–260.

Kneller, Richard, Danny McGowan, Tomohiko Inui, and Toshiyuki Matsuura, "Globalization, Multinationals and Productivity in Japan's Lost Decade," *Journal of Japanese and International Economies*, 2012, *26* (1), 110–128.

Kumano, Yusuke, Ichiro Muto, and Akihiro Nakano, "What Explains the Recent Fluctuations in Japan's Output? A Structural Factor Analysis of Japan's Industrial Production," *Journal of the Japanese and International Economies*, 2014, *34(C)*, 135–153.

Long, John B. Jr. and Charles I. Plosser, "Real Business Cycles," *Journal of Political Economy*, February 1983, *91* (1), 39–69.

Matsuura, Toshiyuki and Kazuyuki Motohashi, "Market Dynamics and Productivity in Japanese Retail Industry in the late 1990's," Discussion papers 05-E-001, Research Institute of Economy, Trade and Industry (RIETI) January 2005.

Miyakawa, Daisuke, Koki Oikawa, and Kozo Ueda, "Misallocation under the Shadow of Death," RIETI Discussion Paper Series 22-E-014, Research Institute of Economy, Trade and Industry (RIETI) Nov 2022.

Moura, Alban, "Investment Shocks, Sticky Prices, and the Endogenous Relative Price of Investment," *Review of Economic Dynamics*, 2018, *27*, 48–63.

Müllar, Ulrich K. and Mark W. Watson, "Testing Models of Low-Frequency Variability," *Econometrica*, 2008, *76(5)*, 979–1016.

__ **and** __ , "Low-Frequency Econometrics," NBER Working Papers 21564, National Bureau of Economic Research, Inc September 2015.

Nakakuki, Masayuki, Akira Otani, and Shigenori Shiratsuka, "Distortions in Factor Markets and Structural Adjustments in the Economy," *Monetary and Economic Studies*, May 2004, *22* (2), 71–99.

Nakamura, Kouji, Souhei Kaihatsu, and Tomoyuki Yagi, "Productivity Improvement and Economic Growth: Lessons from Japan," *Economic Analysis and Policy*, 2019, *62*, 57–79.

Nishimura, Kiyohiko G., Takanobu Nakajima, and Kozo Kiyota, "Does the Natural Selection Mechanism Still Work in Severe Recessions?: Examination of the Japanese Economy in the 1990s," *Journal of Economic Behavior & Organization*, September 2005, *58* (1), 53–78.

Rodríguez-López, Jesús and José L. Torres, "Technological Sources of Productivity Growth in Germany, Japan, and The United States," *Macroeconomic Dynamics*, 2012, *16*, 133–150.

Takahashi, Yuta and Naoki Takayama, "Hidden Stagflation," Discussion Paper Series 733, Institute of Economic Research, Hitotsubashi University July 2022.

__ **and** __ , "Tech-Driven Secular Stagnation: Cross-Country Evidence," Discussion Paper F Series 1171, Center for International Research on the Japanese Economy, The University of Tokyo March 2022.

vom Lehn, Christian and Thomas Winberry, "The Investment Network, Sectoral Comovement, and the Changing U.S. Business Cycle," *The Quarterly Journal of Economics*, 2022, *137* (1), 387–433.

Watanabe, Shingo, "Investment-Specific Technology Shocks Revisited," IMES Discussion Paper Series 20-E-08, Institute for Monetary and Economic Studies, Bank of Japan June 2020.

Yagi, Tomoyuki, Kakuho Furukawa, and Jouchi Nakajima, "Productivity Trends in Japan – Reviewing Recent Facts and the Prospects for the Post-COVID-19 Era –," Bank of Japan Working Paper Series 22-E-10, Bank of Japan July 2022.

A JIP Database

The JIP database contains quantity and price indices for inputs and outputs across industries.[33] The growth rate of any one industry's aggregate is defined as a Divisia index given by the value-share weighted average of its disaggregated component growth rates. Labor input is differentiated by gender, age, education, and employment status. Labor input growth is then defined as a weighted average of growth in annual hours worked across all labor types using labor cost shares of each type as weights. Specifically, labor input growth is expressed as follows.

$$\Delta \ln L_{i,\tau} = \sum_{k} \frac{w_{i,k,\tau} MH_{i,k,\tau}}{\sum_k w_{i,k,\tau} MH_{i,k,\tau}} \Delta \ln MH_{i,k,\tau}, \tag{17}$$

where $L_{i,\tau}$ is labor input index for industry i, $MH_{i,k,\tau}$ is annual hours of attribute k workers in industry i, $w_{i,k,\tau}$ is the hourly labor cost of attribute k workers in industry i, in period τ.

As for TFP for industry i, we use the value-added Solow residuals defined below.[34]

$$\Delta \ln a_{i,\tau} = \Delta \ln g_{\tau}^{va} - \bar{u}_{i,L} \Delta \ln L_i - \bar{u}_{i,K} \Delta \ln K_i, \tag{18}$$

where g^{va} is the real value added calculated using the Laspeyres chain method, and $\bar{u}$ is the average of each factor's cost share in the total labor and capital costs for period τ and $\tau - 1$.

B Estimation of the factor model

Following Foerster et al. (2022), this section describes the estimation of the factor model. See also Appendix 1 of Foerster et al. (2022) for more details.

B.1 A low frequency factor model

The trends extracted using Müllar and Watson (2008)'s method are weighted averages of cosine functions. We refer to the weights that characterize such low-frequency trends as cosine transforms and represent them as a $q \times 1$ vector. For instance, (2) in the main text shows that the cosine transforms for $\Delta \ln l_{i,\tau}$ and $\Delta \ln a_{i,\tau}$ are $\boldsymbol{\Phi}_{\boldsymbol{i}}^{\boldsymbol{l}} = [\phi_{i,1}^{l}, \phi_{i,2}^{l}, ..., \phi_{i,q}^{l}]'$ and $\boldsymbol{\Phi}_{\boldsymbol{i}}^{\boldsymbol{a}} = [\phi_{i,1}^{a}, \phi_{i,2}^{a}, ..., \phi_{i,q}^{a}]'$, respectively.

[33] See Fukao et al. (2007) and Fukao, ed (2021) for a more detailed discussion.

[34] Since capital investment by industry in growth accounting is used only in the calculation of TFP in our analysis, we will refrain from a detailed explanation, but here we describe only points to be noted when linking JIP2015 and JIP2023. One difference between the two is that JIP2023 is revised to add R&D investment in response to the 2008 SNA, while JIP2015 is not. Due to data limitations, we assume that these differences do not affect the year-on-year values, which are used in the analysis, and calculate the year-on-year ratios for both and then simply connect them (note that since the coverage periods of JIP2015 and JIP2023 partially overlap, the level differences between the two do not affect the analysis). As in the JSNA, output is constructed from the supply tables of the input-output table in the form of Laspeyres chain real indices (intermediate input is constructed from the use tables).

Now, we can express the factor model of (3) in terms of cosine transforms as follows.

$$\begin{bmatrix} \boldsymbol{\Phi}_i^l \\ \boldsymbol{\Phi}_i^a \end{bmatrix} = \begin{bmatrix} \lambda_i^l \boldsymbol{I}_q & \mathbf{0} \\ \mathbf{0} & \lambda_i^a \boldsymbol{I}_q \end{bmatrix} \begin{bmatrix} \boldsymbol{F}^l \\ \boldsymbol{F}^a \end{bmatrix} + \begin{bmatrix} \boldsymbol{E}_i^l \\ \boldsymbol{E}_i^a \end{bmatrix}, \tag{19}$$

where $\boldsymbol{F}_i^l$, $\boldsymbol{F}_i^a$, $\boldsymbol{E}_i^l$, $\boldsymbol{E}_i^a$, and $\boldsymbol{I}_q$ are cosine transforms of unobserved common factors (f_τ^l, f_τ^a) and industry-specific disturbances $(\epsilon_{i,\tau}^l, \epsilon_{i,\tau}^a)$, and a unit matrix of q, respectively. Müllar and Watson (2015) argue that the cosine transforms $(\boldsymbol{\Phi}_i^l, \boldsymbol{\Phi}_i^a, \boldsymbol{F}^l, \boldsymbol{F}^a, \boldsymbol{E}_i^l, \boldsymbol{E}_i^a)$ is approximately normally distributed when T is large, so that we can estimate (19) by standard factor analysis methodology when we parametrize the covariance matrices. Specifically, Foerster et al. (2022) specify that the covariance matrix of a generic cosine transform $\boldsymbol{X}$ takes a following form of two parameters (σ_X^2, γ_X),

$$Var(\boldsymbol{X}) = \sigma_X^2 D(\gamma_X) \tag{20}$$

where $D(\gamma_X)$ is a diagonal matrix whose j's diagonal element is $1 + \gamma_X^2 (j\pi)^{-2}$. The two parameters σ_X^2 and γ_X correspond to variability and persistence of low frequency trend, respectively.

We assume that the common factors and industry-specific factors are uncorrelated, and an industry-specific factor in an industry are uncorrelated with those in other industries. Whereas, the common factors $\boldsymbol{F}^l$ and $\boldsymbol{F}^a$ are allowed to be correlated. The covariance is parametrized as $Cov(\boldsymbol{F}^l, \boldsymbol{F}^a) = \sigma_{F^l,F^a} D(\gamma_{F^l})^{1/2} D(\gamma_{F^a})^{1/2}$. Analogously, the industry-specific factors within an industry are correlated and the covariance is parameterized in the same manner.

B.2 Bayes estimation

We have three sets of parameters to estimate: the factor loadings $(\boldsymbol{\lambda}^l, \boldsymbol{\lambda}^a)$, the covariance matrices $\boldsymbol{\Sigma_F}$ and $\boldsymbol{\Sigma_{E,i}}$, and the persistence parameters $\gamma_{\boldsymbol{F}} = (\gamma_{\boldsymbol{F}^l}, \gamma_{\boldsymbol{F}^a})$ and $\gamma_{\boldsymbol{E},i} = (\gamma_{\boldsymbol{E}_i^l}, \gamma_{\boldsymbol{E}_i^a})$ for $i = 1, 2, ..., K$ where

$$\boldsymbol{\Sigma_F} \equiv \begin{bmatrix} \sigma_{F^l}^2 & \sigma_{F^l,F^a} \\ \sigma_{F^l,F^a} & \sigma_{F^a}^2 \end{bmatrix}, \quad \boldsymbol{\Sigma_{E,i}} \equiv \begin{bmatrix} \sigma_{E_i^l}^2 & \sigma_{E_i^l,E_i^a} \\ \sigma_{E_i^l,E_i^a} & \sigma_{E_i^a}^2 \end{bmatrix}.$$

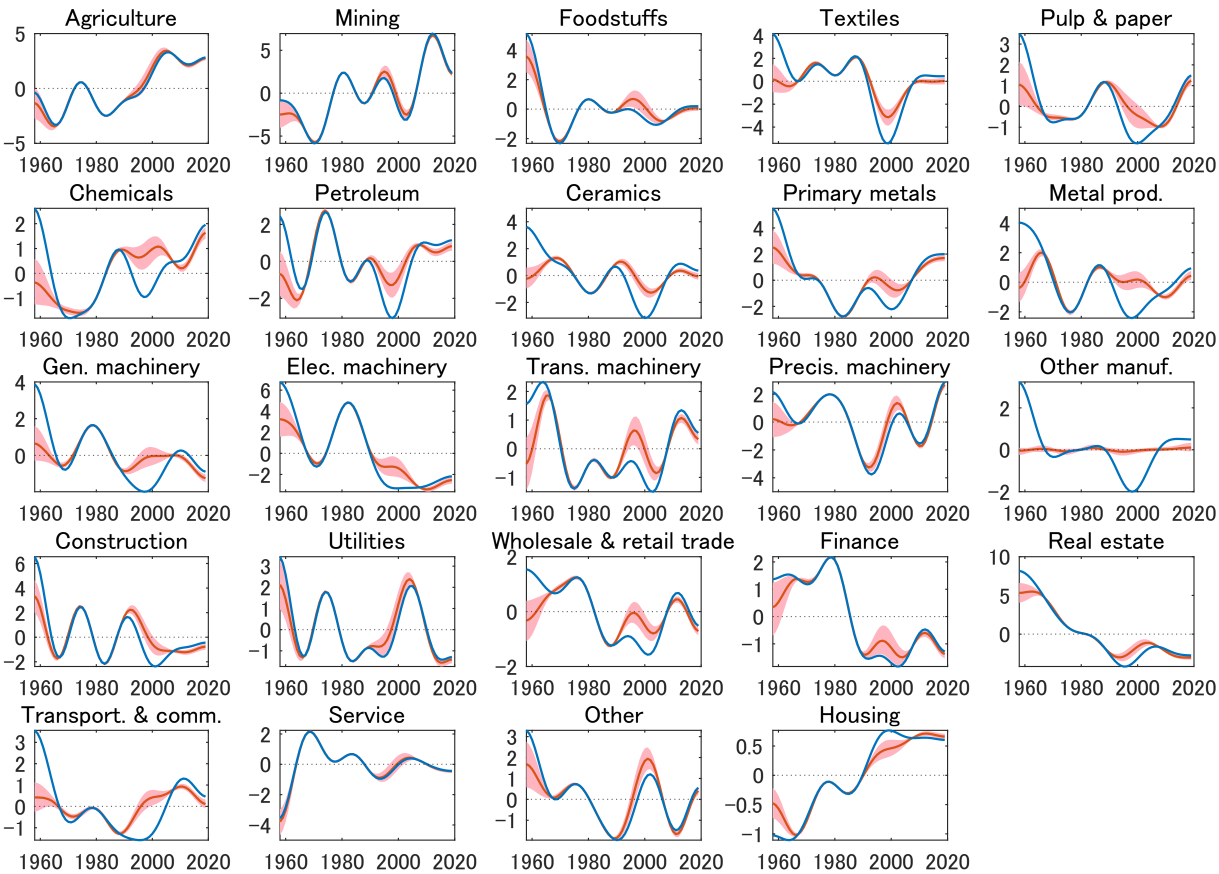
The priors for the factor loadings are described in the main text. The priors for $\boldsymbol{\Sigma_F}$ and $\boldsymbol{\Sigma_{E,i}}$ are an invert Wishart with $\nu = 0.01$ degrees of freedom and scale $\nu \boldsymbol{I_2}$. The priors for $\ln(\gamma_{\boldsymbol{F}})$ and $\ln(\gamma_{\boldsymbol{E},i})$ are uniform distribution of $U(0, \ln(500))$. Using Foerster et al. (2022)'s code, we approximate this prior by a 15-point equally-spaced grid between 0 and $\ln(500)$.

The Markov chain monte carlo method is used to build posterior distribution. The specific algorithm is Gibbs sampler. In the main text, the number of draws is 550,000. The first 50,000 draws are discarded as burn-in and every 200th draws of the remaining draws are saved for posterior analysis.

C Credible band of the estimated industry-specific factors.

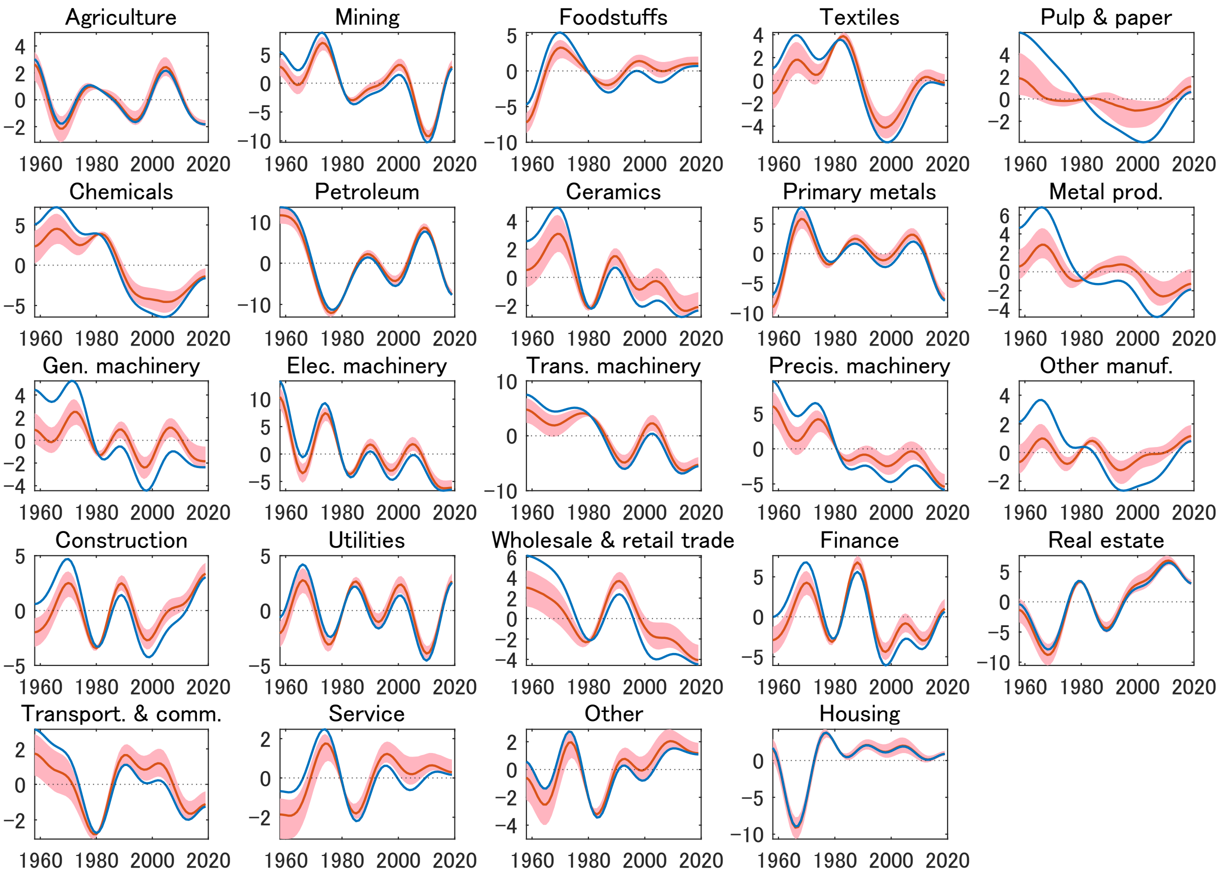
The following figures present the posterior median and 68% credible intervals of industry-specific factors in labor and TFP trend growth rates.

Figure 18: Labor trends and industry-specific components



Percentage points at annual rate. Each panel shows the low-frequency trend for industry growth rate (in blue) and its industry-specific component (in red). The red lines denote the posterior median and the shaded areas the (pointwise) equal-tail 68% credible intervals.

Figure 19: TFP trends and industry-specific components



Percentage points at annual rate. Each panel shows the low-frequency trend for industry growth rate (in blue) and its industry-specific component (in red). The red lines denote the posterior median and the shaded areas the (pointwise) equal-tail 68% credible intervals.

D US data of working age population

The analysis for the US primarily follows Foerster et al. (2022). However, to make the results comparable with those for Japan, we converted the variables to a per working-age population basis, just as we did for the Japan's data. For the US, the data of a working-age population is available starting from 1955. For the earlier period, from 1947 to 1954, we constructed per working-age population data using the following method.

From 1955 to the current, we use the working-age population from FRED (LFWA64TTUSA647N). From 1950 to 1954, we backcast the working-age population using the growth rate of the estimated working age population in "Current population report: population estimates Table 1," September 27 1955., US Department of Commerce. From 1947 to 1949, we backcast the working-age population using the growth rate of total population of the US.