The 7th World KLEMS Conference

Manchester, UK

12-13 October, 2022

Covid-19 Pandemic and TFP in the Quarterly Model of Korea(2012-2022)

Hak K. Pyo | Professor Emeritus, Seoul National University

Keunhee Rhee | Institute of Economic Research, SNU

Yoojin Bin | Graduate School of International Studies, SNU

Contents

1. Introduction

- Increasing demand for high-frequency measures of technology shocks and change and to asses trends in potential output because of ICT-related technological advances and their fast spread within industries and across industries
- There is also a new real-time need to measure the Solow residual at the time of real-sector or financial crisis
- The COVID-19 Pandemic has caused a global recession and fiscal expansion on a global scale from the first quarter of 2020(Pyo, 2021)
- Relatively crude measures of TFP are easy to construct with annual data, for example, multifactor productivity estimated by the BLS and EU KLEMS project.
- But the necessary data to estimate short-term high frequency technology measure are only available with a long lag. The KLEMS-type industry-level measure of productivity for short-years in official data-release and due to intensive and extensive data work to construct KLEMS-type estimates including quality index of labor inputs and decomposed capital stocks

1. Introduction

- This paper constructs a new real-time quarterly growth-accounting database for the Republic of Korea following up Ahn, Han and Pyo (2019).

➢ Firstly, it differs from Fernald (2014) in defining the sectors to be covered in actual growth accounting. Fernald (2014) constructs a quarterly database for the U. S. business sector while this paper constructs a quarterly database for both business sector and non-business (public) sector.

➢ The second difference lies in the way the variations in factor utilization (capital utilization and work intensity) are measured. Fernald(2014) estimates "purified" Solow residuals by estimating a Hall (1990)-style regression on industry-level data and applying the estimation methods by Basu, Fernald, and Kimball (2006). But we use observed capacity utilization index to measure capital utilization in Manufacturing and electricity consumption in Service following Jorgenson and Griliches (1997), Zaid and Bodger (2005) and Pyo and Song (2014). Basu, Fernald and Kimball (2006) also notes that electricity use might proxy for true capital services and it might be reasonable for some manufacturing industries but it ignores labor effort. Therefore, we have used the ratio of overtime working hours in total working hours as a separate proxy for effort per unit of labor. We have used the ratio of overtime working hours in total working hours as a proxy for effort per unit of labor.

1. Introduction

➢ The third difference is that while Fernald (2014) includes consumer durables in the investment sector, we do not include consumer durables in the investment sector which consists of business equipment and structures and intellectual property investment.

- Since our measurement of value-added is based on Bank of Korea's national accounts statistics, the measurement of investment is limited to capital formation in business and government sector and therefore, we have not included consumer durables as part of investment.
- We have also estimated a quarterly regression model to supplement our findings from quarterly growth accounting model. The regression of labor productivity on capital-labor ratio after imposing the constant-returns-to-scale (CRS) restriction estimates the share of factor inputs and the growth rate of neutral technical progress (TFP). By using a dummy variable to control the pandemic period from the first quarter of 2020 to the first quarter of 2022, we have identified the shift in labor productivity during the pandemic period.

1. Introduction

- This paper intends to report a preliminary KLEMS-type industry-level Quarterly Database for Korea (2012 First quarter-2022 First Quarter) which are consistent with its National Accounts Statistics. We have used quarterly interpolation and seasonal adjustments using various monthly or quarterly data on value-added, investment and hours worked to construct KLEMS-type quarterly database which is consistent with its annual counterparts. We also apply the database to conduct a quarterly growth accounting for the Korean economy and estimate quarterly total factor productivity by industries.
- Fernald (2014) estimated a quarterly growth-accounting database for the US business sector and produced the quarterly TFP series of which annualized growth rate is very close to the growth rate of the BLS (2009) Multifactor Productivity measure for the US private business sector. The correlation between annual changes in the two US series is reported to be 0.97.

1. Introduction

- Quarterly capital stock has been generated using segmented linear year-to-year interpolation. Quarterly depreciation has been linearly estimated interpolating the annual depreciation assuming that the annual depreciation is spread equally. Pyo and Song (2014) estimated the quarterly capital stock by distributing the annual gross fixed capital formation by assets and industries by interpolating quarterly weights of cumulated investment as quarterly weights of capital stocks. Quarterly depreciation is assumed to be the same as annual depreciation.

- We find the quarterly database and the resulting estimates of TFP provide us with a very useful information throughout the COVID-19 pandemic period. Before the pandemic, the Korean economy is observed to have gone through a very rapid period of productivity convergence as observed in Pyo (2018) and Rhee and Pyo (2022).

1. Introduction

- The major findings are that the COVID-19 after the first quarter of 2020 has made growth rates of both GDP and labor input turn negative. But the relative contribution of capital input and TFP make up almost 90 % of GDP growth. We also find the quarterly TFP estimates are exhibiting a pro-cyclical pattern which is closely related to the recovery cycle of the pandemic. This finding is in contrast with the finding by Basu, Fernald and Kimball (2006) who supports technology improvements are contractionary: when technology improves, inputs and investment generally fall in the short run, and output itself may also fall.

2. A Quarterly Growth Accounting Model

- Aggregate production function from Fernald(2014)

$$Y_t = F(\, Z_t K(K_{1,t-1},\, K_{2,t-1}, \ldots\ldots K_{j,t-1}),\; E_t L\,(H_{1t},\, H_{2t}, \ldots\ldots H_{jt}),\; A_t) \qquad (1)$$

where K: j-type capital stock's capital service flow
Z: Capital utilization rate
L: Labor input (Aggregate Working Hours, Hj)
E: Effort per unit of labor
A: Technological change

$$\Delta lnTFP_{it} = \Delta lnV_{it} - \sum_{X=L,K} \overline{V_{X,t}}\, \Delta X_{it} \qquad (2)$$

V: Value-added
X: Factor inputs

2. A Quarterly Growth Accounting Model

- Assuming perfect competition, a differentiation of production function:

$$\Delta lnY = [(\alpha \Delta lnK \; - (1-\alpha)\Delta lnL) + \Delta lnU + \Delta lnA] \quad (3)$$

where $\Delta lnU = \alpha \Delta lnZ - (1\text{-}\alpha)\Delta lnE$

$$\Delta lnTFP = \Delta lnY - \alpha \Delta lnK - (1\text{-}\alpha)\Delta lnL \quad (4)$$

- Utilization-adjusted TFP growth

$$\Delta lnTFP - \text{util} = \Delta lnTFP - \Delta lnU \quad (5)$$

where $\Delta lnU = \alpha \Delta lnZ - (1\text{-}\alpha)\Delta lnE$

3. Data and Methodologies

(1) GDP

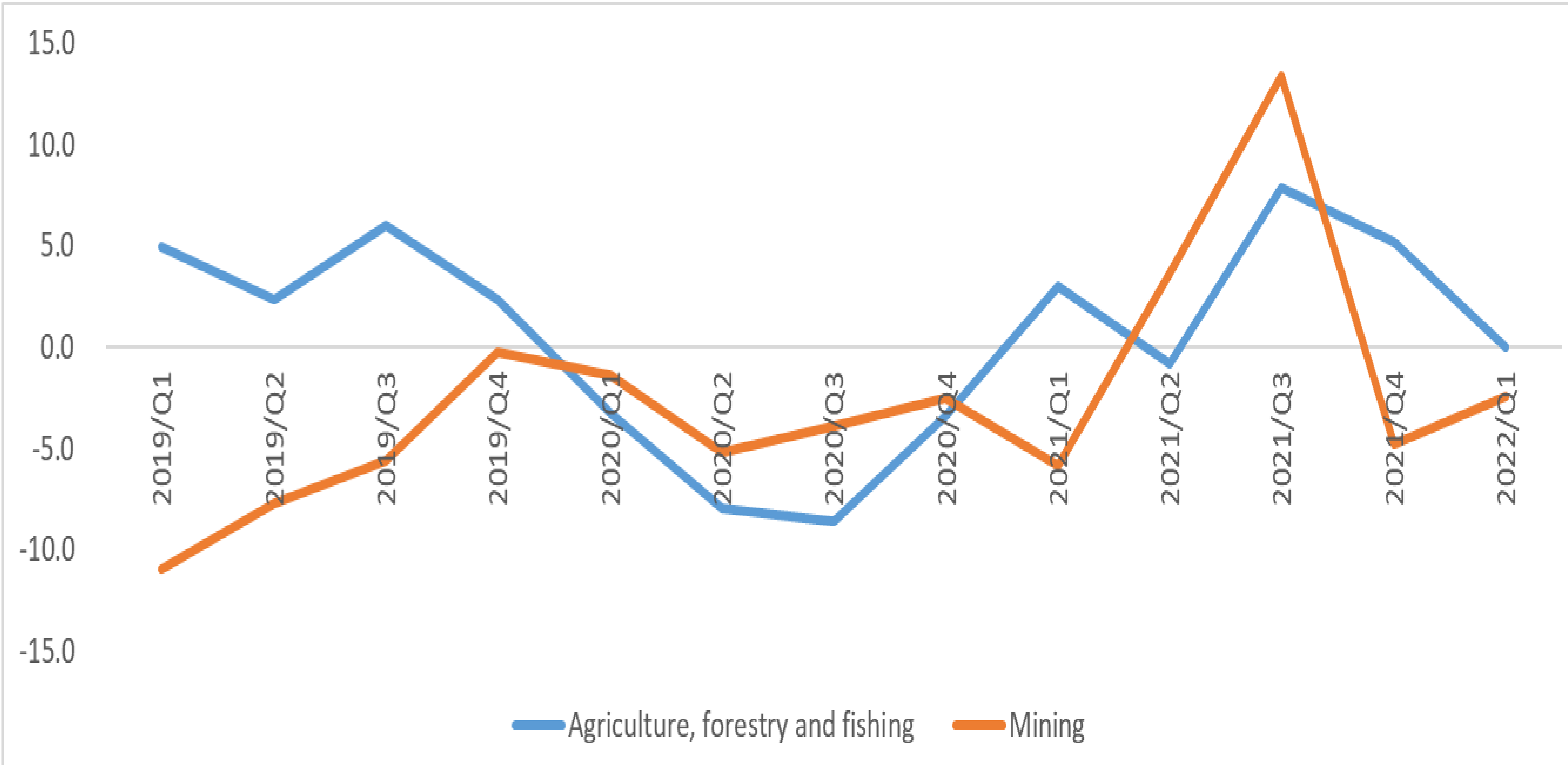
- As shown in Figure 1- 4, quarterly real GDP data by sector shows a deep downturn starting from the first quarter of 2020 when Covid-19 Pandemic has erupted in Korea.

  In case of Manufacturing, the recovery started from the second quarter of 2020 but the contraction came a year later starting from the third quarter of 2021. We note a lot more volatility in the subsectors' quarterly GDP series.

- In particular, Accommodation/Food, Transportation/storage and Cultural/Other services sector had the largest volatility.

3. Data and Methodologies

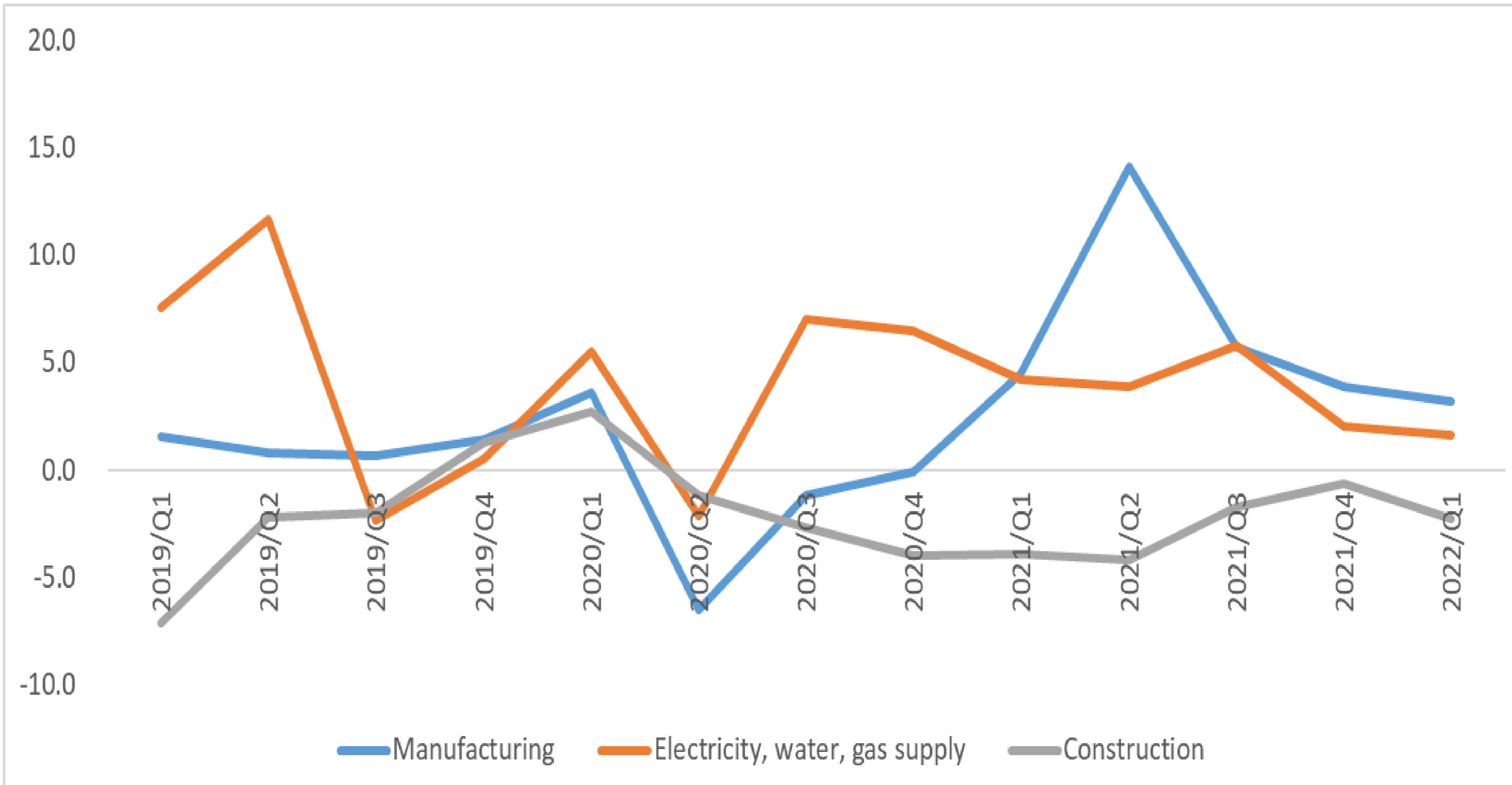
(Figure 1) Quarterly GDP Growth Rate(%, Primary Industry, 2019.1 ~ 2022.1)



Source: Bank of Korea(ecos.bok.or.kr)

3. Data and Methodologies

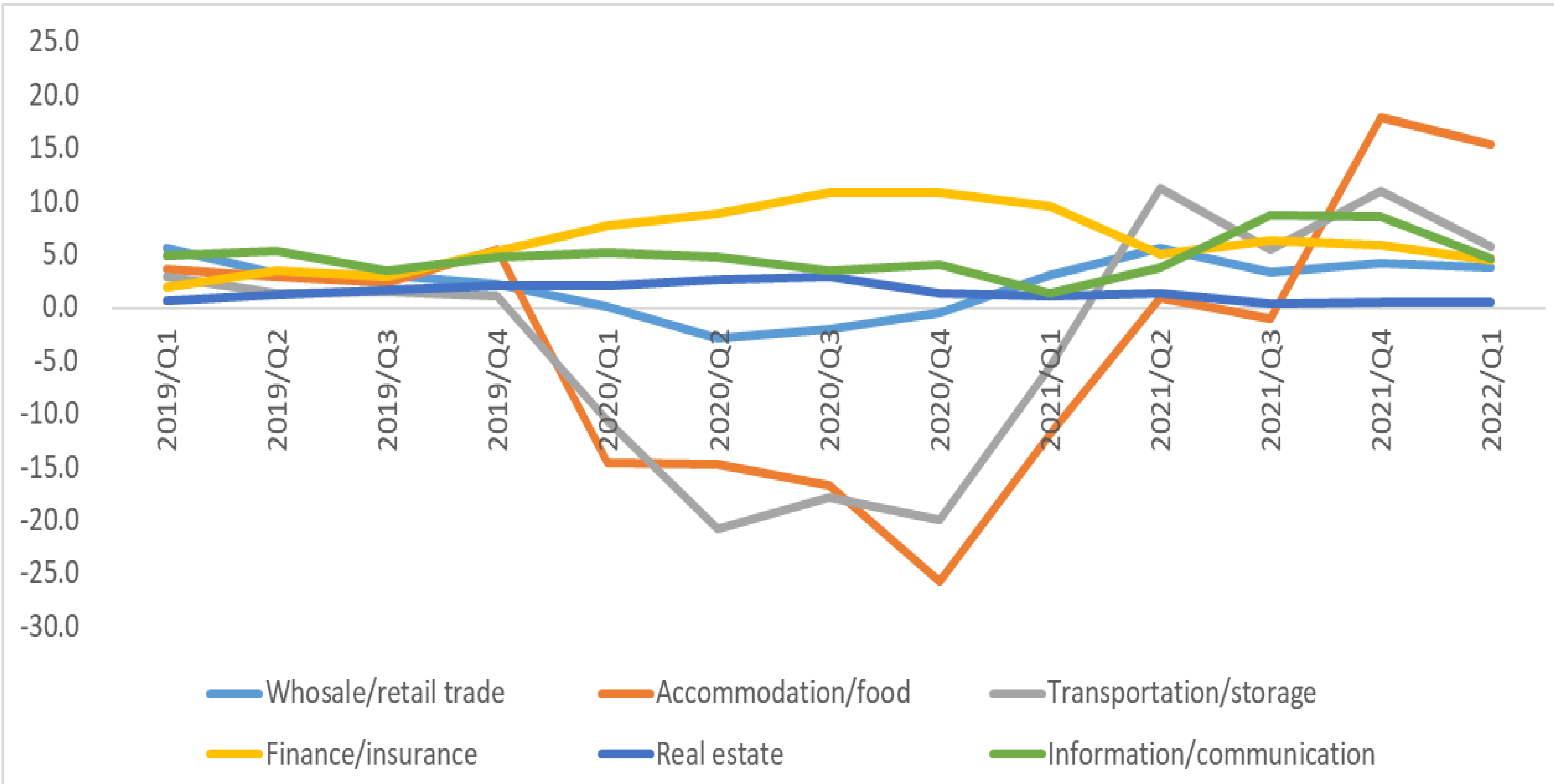
(Figure 2) Quarterly GDP Growth Rate(%, Secondary Industry, 2019.1 ~ 2022.1)



Source: Bank of Korea(ecos.bok.or.kr)

3. Data and Methodologies

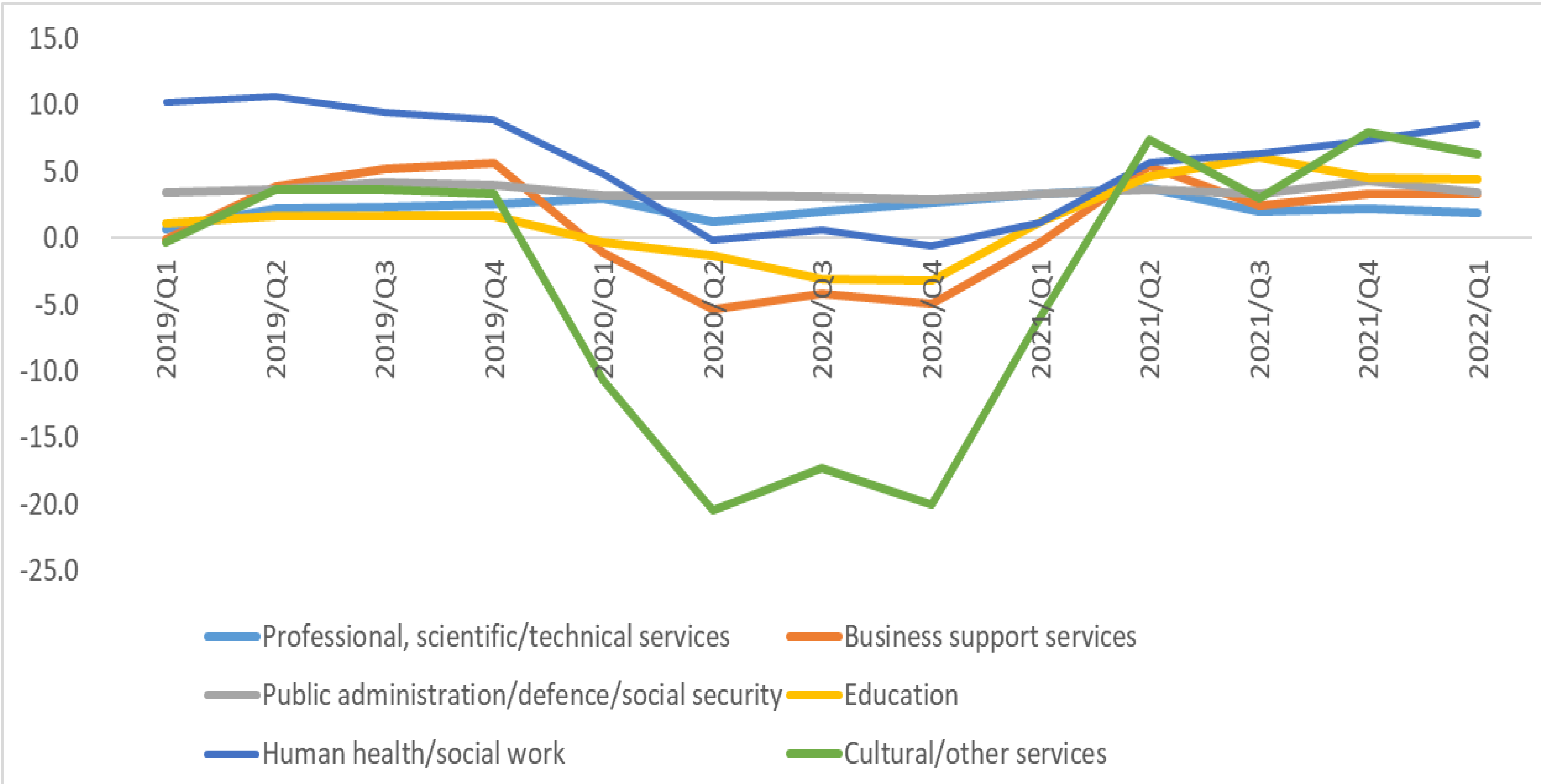
(Figure 3) Quarterly GDP Growth Rate(%, Service Industry, 2019.1 ~ 2022.1)



Source: Bank of Korea(ecos.bok.or.kr)

3. Data and Methodologies

(Figure 4) Quarterly GDP Growth Rate(%, Service Industry, 2019.1 ~ 2022.1)



Source: Bank of Korea(ecos.bok.or.kr)

3. Data and Methodologies

(2) Capital Stock

- By utilizing the quarterly share of investments on each asset as a weight, we have converted the annual gross fixed capital formation by assets and industries to quarterly investments. Then we have estimated the quarterly capital stock by applying the modified Perpetual inventory method as follows:

$$K_{t+k} = K_t + \frac{I_{t+k}}{I_{t+4}} (K_{t+4} - K_t)$$

$$= K_t + \frac{I_{t+k}}{I_{t+4}} (I_{t+4} - \delta K_t)$$

$$= (1 - \frac{I_{t+k}}{I_{t+4}} \delta) K_t + I_{t+k}$$

$$\therefore K_{t+4} = K_t (1-\delta) + I_{t+4} \qquad (6)$$

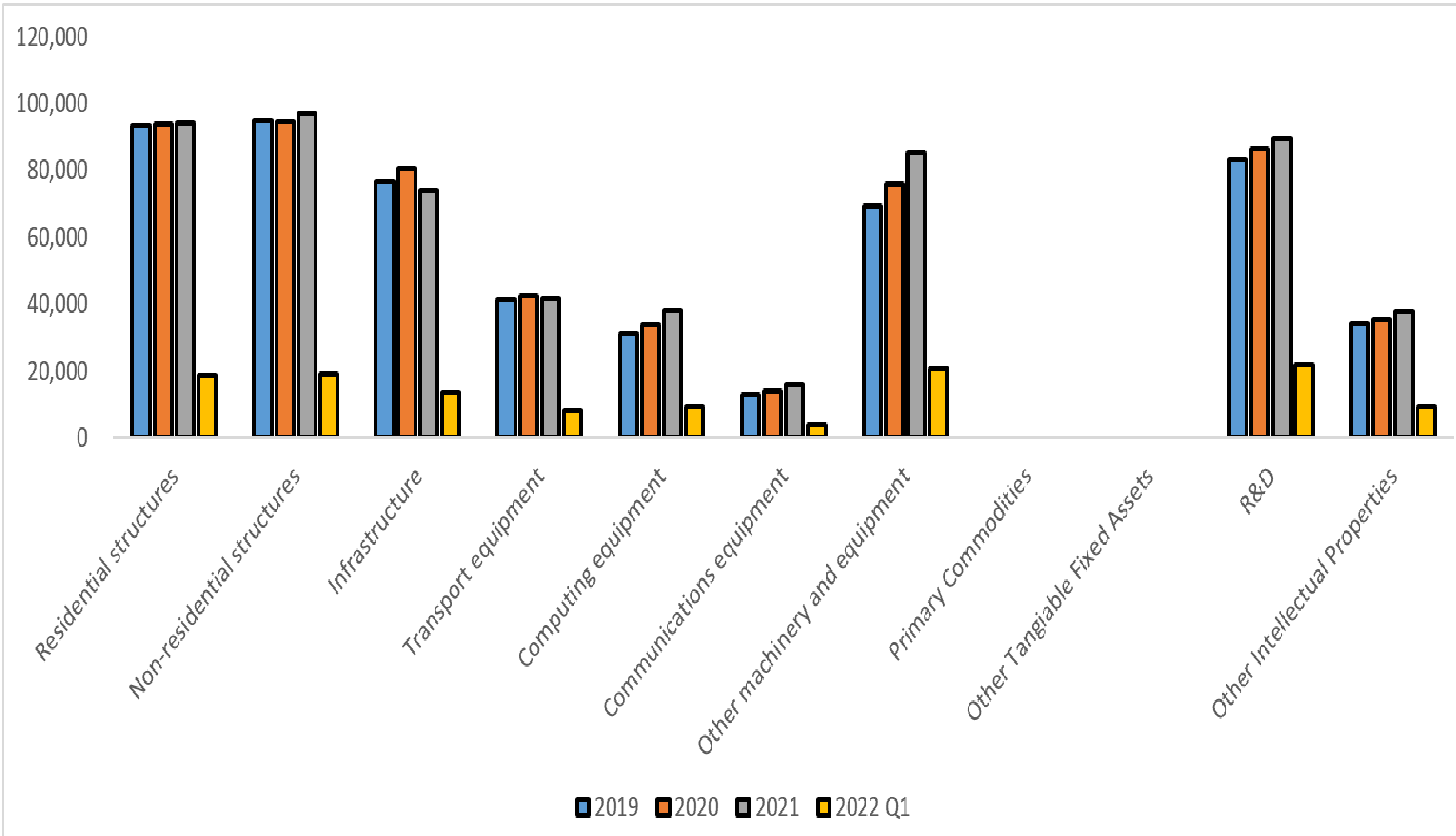
where K_t =capital stock in t quarter

I_t = capital formation in t quarter

3. Data and Methodologies

(Figure 5) Gross Fixed Capital Formation (2019.1 ~ 2022.1)

<Bill. KRW)



Source: Bank of Korea(ecos.bok.or.kr)

3. Data and Methodologies

(Table 1) Gross Fixed Capital Formation (2019.1 ~ 2022.1)

<Trillion KRW)

EUKLEMS	2020 Capital Stock	2021 Capital Fixed Formation	2020 Capital Stock* Rate of depreciation	2021 Capital Stock
Residential structures	1,757	94	58	1,793
Non-residential structures	1,332	97	40	1,389
Infrastructure	1,490	74	37	1,527
Transport equipment	225	42	38	229
Computing equipment	164	38	15	187
Communications equipment	108	16	10	114
Other machinery and equipment	553	85	51	588
Primary Commodities	0	0	0	0
Other Tangible Fixed Assets	0	0	0	0
R&D	252	89	79	262
Other Intellectual Properties	106	38	33	110

3. Data and Methodologies

(Table 2) Estimates of Depreciation Rates by Types of Assets

<%>

Types of Assets	Depreciation Rate
Residential structures	3.3
Non-residential structures	3.0
Infrastructure	2.5
Transport equipment	16.9
Computing equipment	9.2
Communications equipment	9.2
Other machinery and equipment	9.2
Primary Commodities	0.0
Other Tangible Fixed Assets	0.0
R&D	31.5
Other Intellectual Properties	31.5

Source: Pyo and Song(2014)

3. Data and Methodologies

(Table 3) Estimates of Annual Capital Stock by Types of Assets (2019 ~ 2022.Q1)

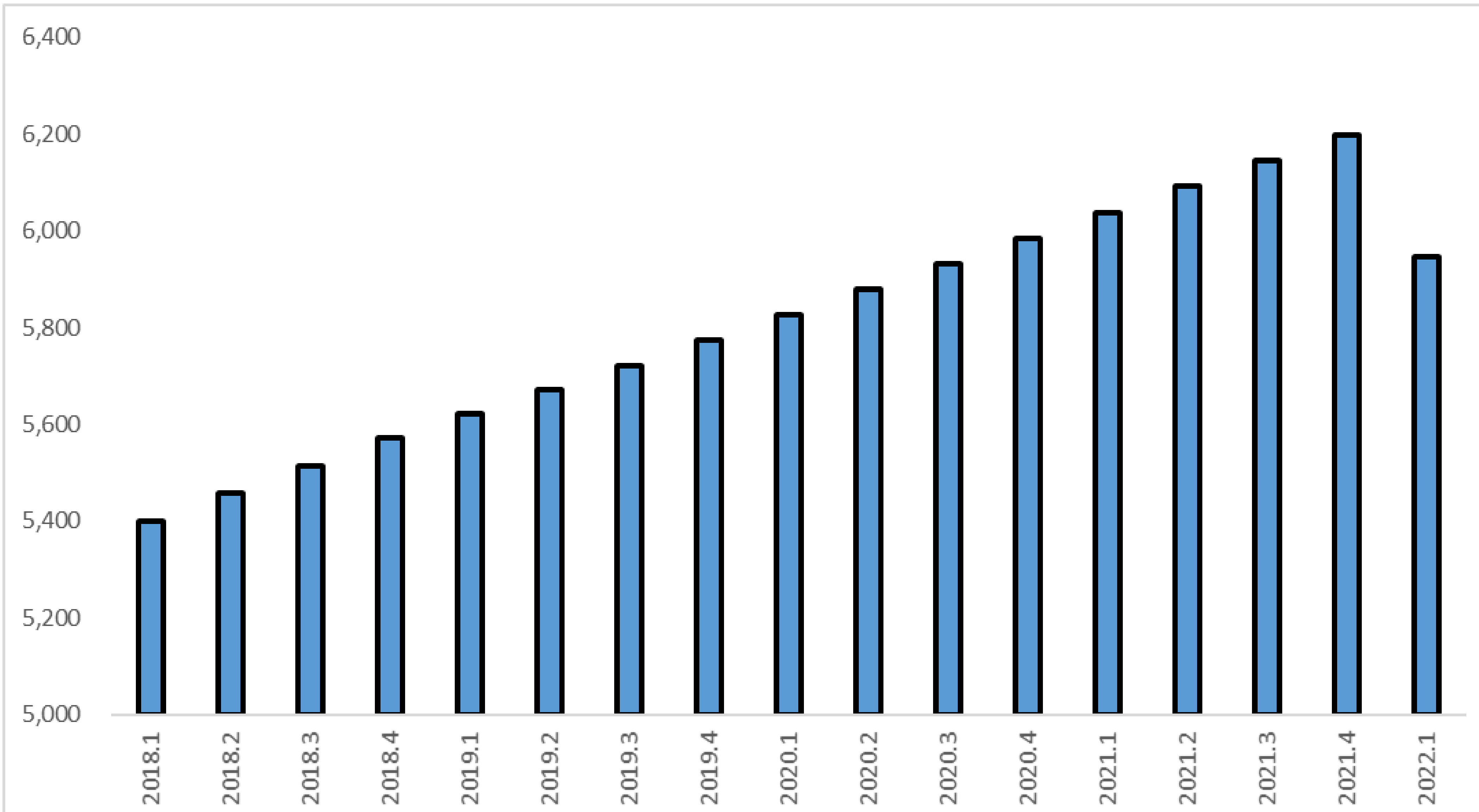
<Trillion KRW)

	2019	2020	2021	2022 Q1
Residential structures	1,719	1,757	1,793	1,752
Non-residential structures	1,275	1,332	1,389	1,366
Infrastructure	1,445	1,490	1,527	1,502
Transport equipment	220	225	229	198
Computing equipment	143	164	187	179
Communications equipment	103	108	114	107
Other machinery and equipment	526	553	588	554
Primary Commodities	0	0	0	0
Other Tangible Fixed Assets	0	0	0	0
R&D	241	252	262	201
Other Intellectual Properties	102	106	110	85

3. Data and Methodologies

(Figure 6) Estimates of Quarterly Capital Stock (2018.Q1 ~ 2022.Q1)

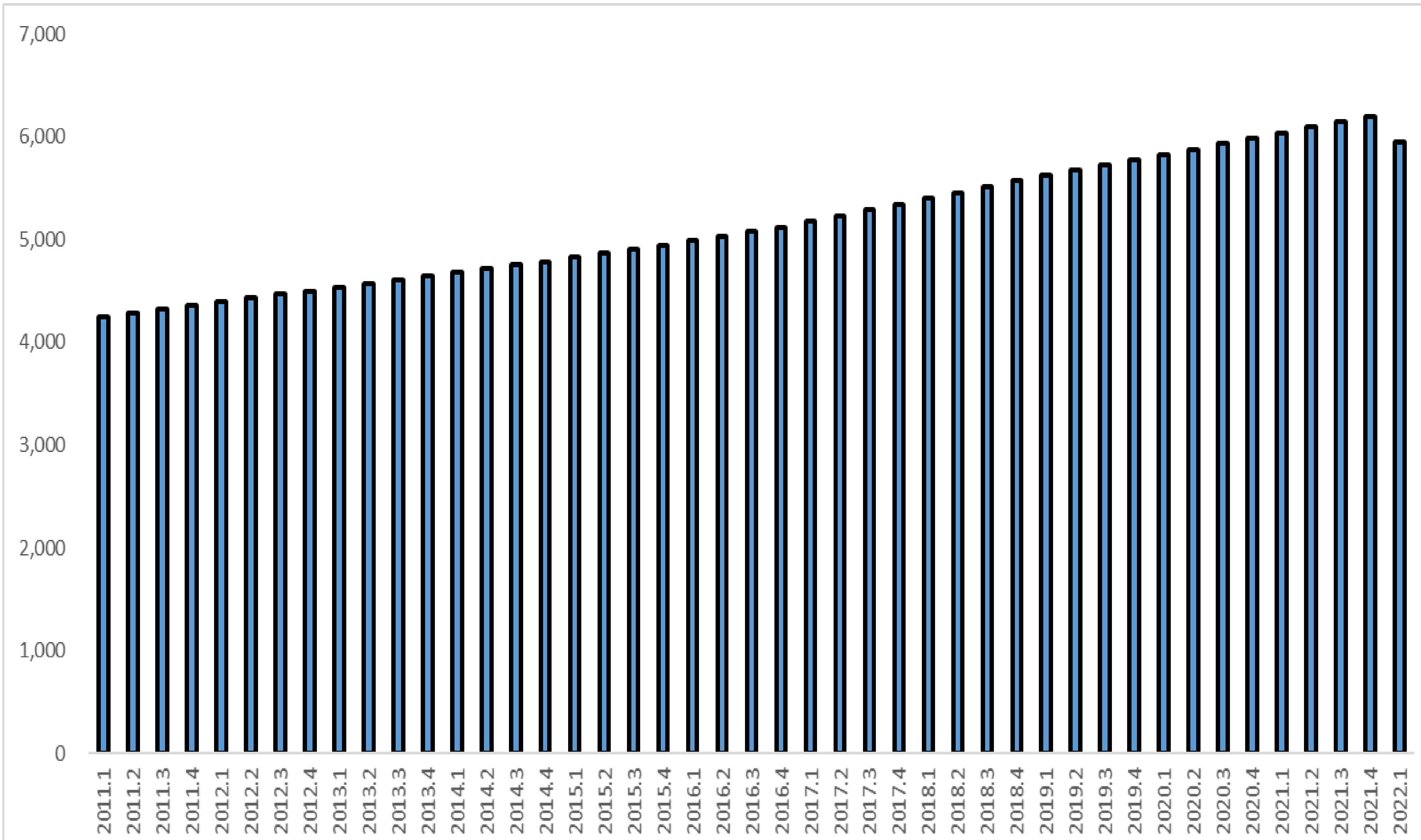
<Trillion KRW)



3. Data and Methodologies

(Figure 7) Estimates of Annual and Quarterly Capital Stock (2011.Q1 ~ 2022.Q1)

<Trillion KRW)



3. Data and Methodologies

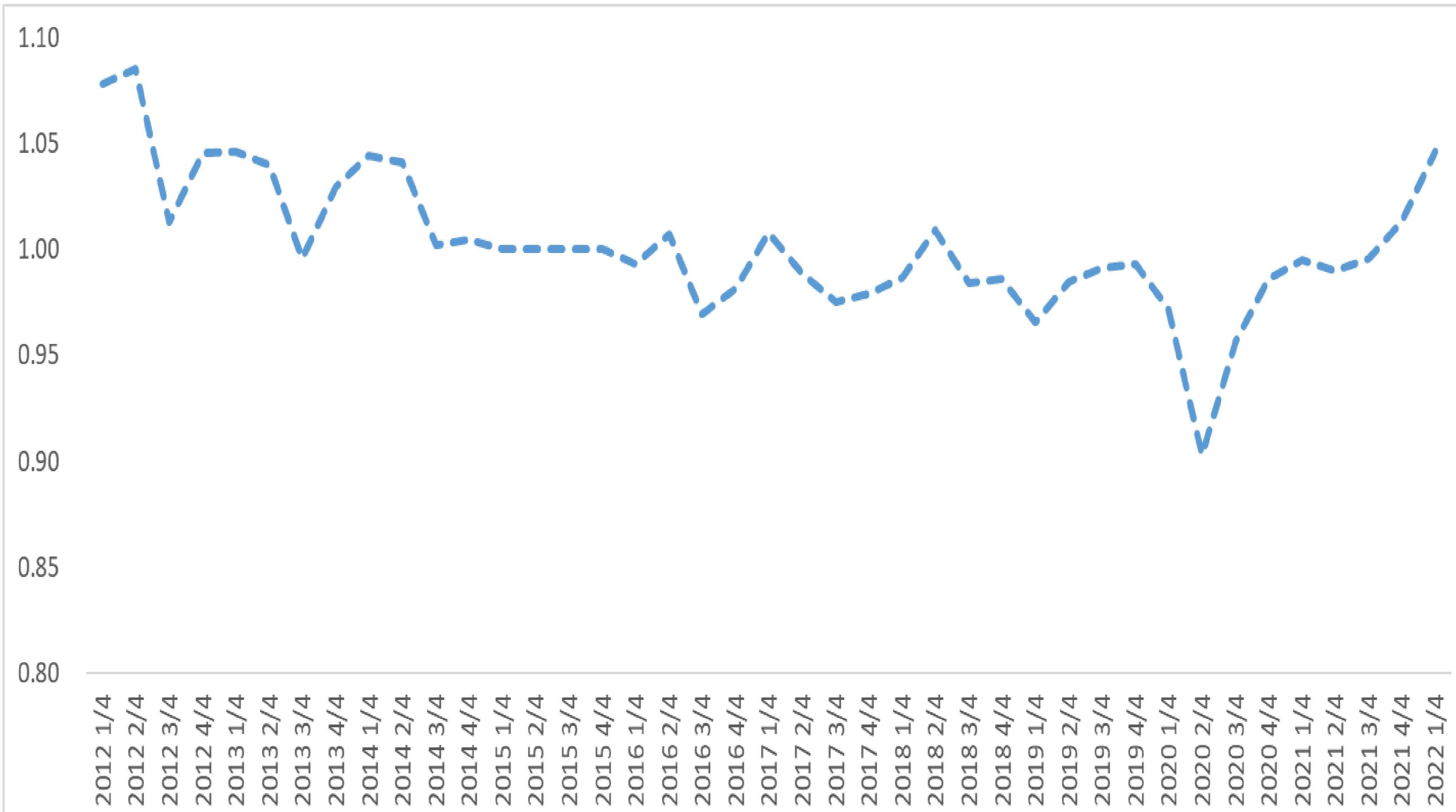
- While Fernald estimates utilization by the workweek of capital, *Z*t (e.g. varying the number of shifts) and by effort required of employees per hour of work *E*t through the regression method in Basu, Fernald and Kimball (2006), we estimated two utilization rates by employing proxy variables directly.

- For capital utilization rate (*Zt),* we have adopted capacity utilization index by Statistics Korea for 21 Manufacturing industries with using 2015 as the base year. Following Pyo and Song (2014), we have used monthly electricity consumption statistics by Korea Energy Economics Institute(KEEI) as a proxy variable for non-manufacturing industries such as Agriculture and Forestry, Mining, and Service industries using 2015 as the base year.

3. Data and Methodologies

(Figure 8) Capital Utilization Rate for Manufacturing Industry (2012. Q1 ~ 2022.Q1)

<2015=1)

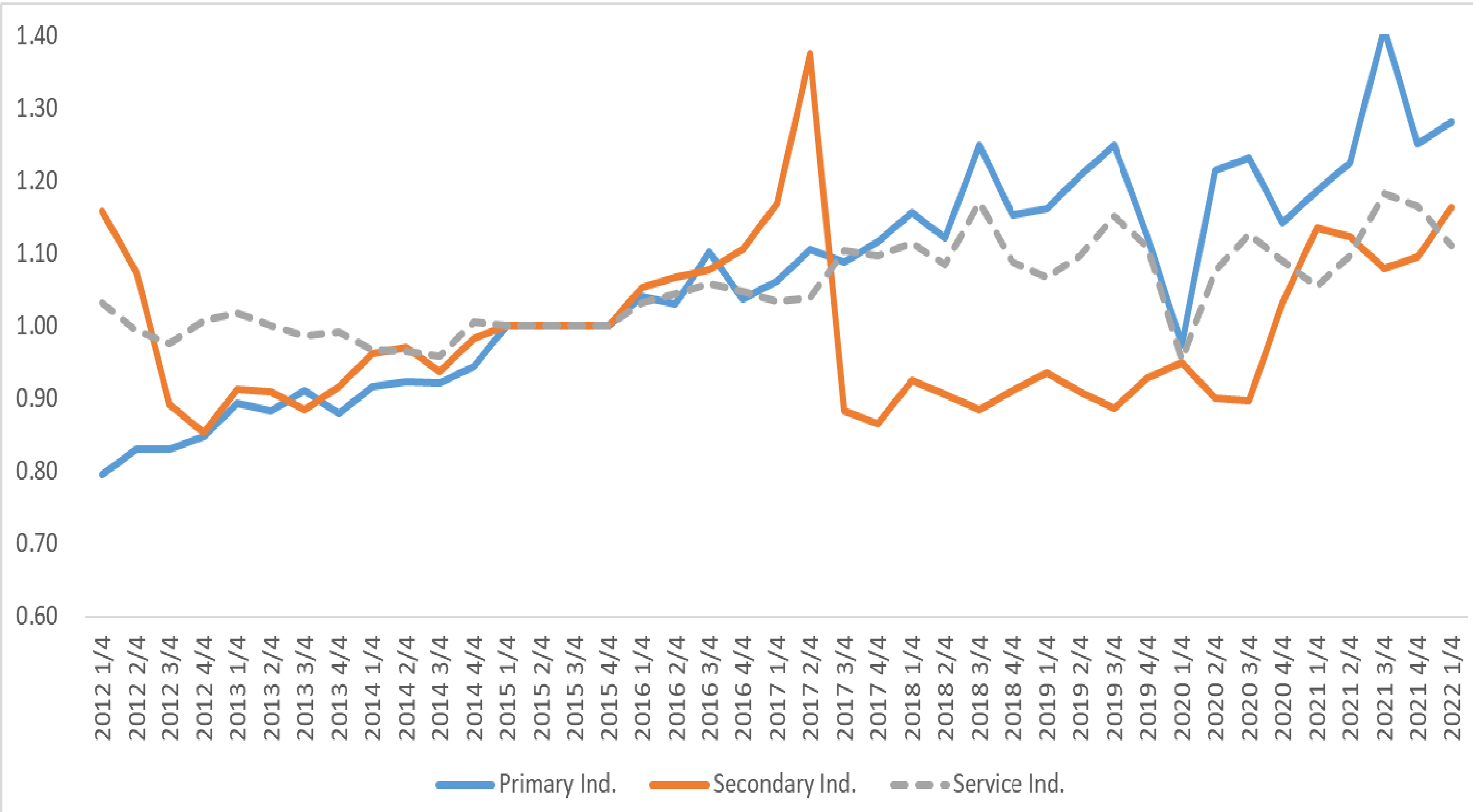


Source: Statistics Korea

3. Data and Methodologies

(Figure 9) Electricity Consumption by Industry Industry (2012. Q1 ~ 2022.Q1)

<2015=1)



Source: Korea Energy Economics Institute (2022)

3. Data and Methodologies

(3) Labor Input

- The estimation of the total hours worked by industries has been conducted as follows. In general, we have the following identity;

$$\sum_{i=1}^{4} qe_i/4 = e \qquad (7)$$

Where qe=quarterly number of workers
e = annual number of workers

- Let's assume that the variation of the quarterly number of workers (*qe*) is same as the variation of the quarterly number of employees (*q*). Then,

$$\frac{qe_i}{\sum_{i=1}^{4} qe_i} = \frac{q_i}{\sum_{i=1}^{4} q_i} \qquad (8)$$

Combining (7) and (8) together, we have

$$\widehat{qe}_i = \frac{q_i}{\sum_{i=1}^{4} q_i} \times \sum_{i=1}^{4} qe_i = \frac{q_i}{\sum_{i=1}^{4} q_i} \times 4e \qquad (9)$$

3. Data and Methodologies

- Fernald(2014) created a quarterly labor- utilization series by using estimated industry coefficients from the regression of the growth rate of value-added ($\Delta \ln Y_i$) on number of hours per unit of labor ($\Delta \ln (H_i/N_i)$) in i-th industry. In our paper, since we do not have quarterly intermediate-inputs data, we adopted the ratio of overtime working hours in total working hours as a proxy variable for work intensity.

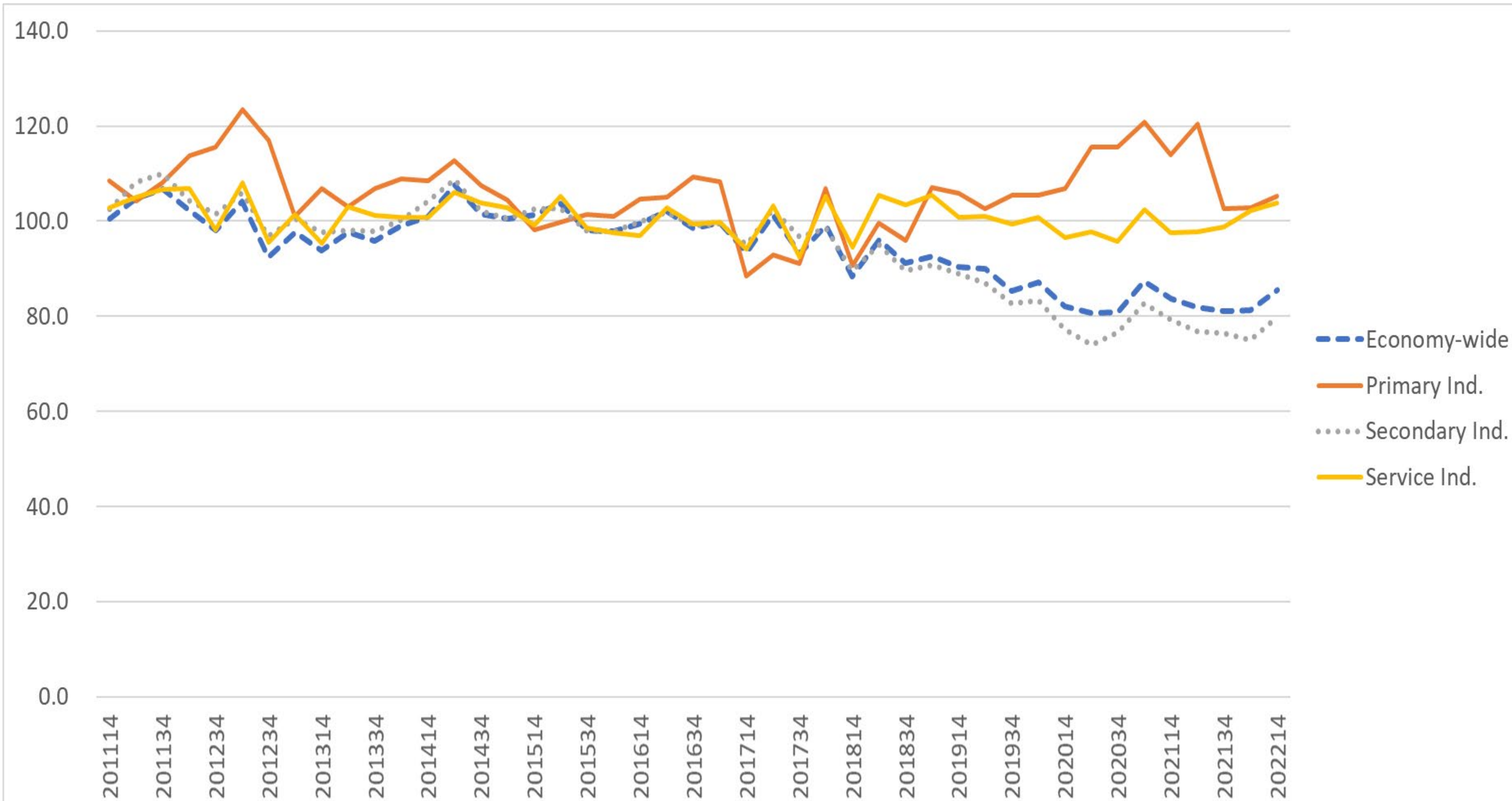
- As shown in Figure 12, the work intensity has been increasing since the base year 2015 and its spread among different industries also became wider than before. It is interesting to note that the breakout of the Covid-19 pandemic has caused a wider spread of work intensity among industries, During Pandemic period, there was a labor law passed in Korean Assembly which limits total working hours per week as 52 hours.

- This new legislation may have forced employers to seek more part-time workers to substitute over-time work demand and have caused work intensity to increase. In particular, in small and medium enterprises (SME), and self-employed shops and restaurants they had to cut or reduce part-time jobs causing work-intensity on the remaining full-time employees increase.

3. Data and Methodologies

(Figure 12) Quarterly Trend of Work Intensity Index (2011 Q1 ~ 2022 Q1)

<2015=100>



Source: Ministry of Employment and Labor, Labor Force Survey at Establishment
Note : Primary Industry includes just Mining industry due to the data limitation

3. Data and Methodologies

(Table 4) Quarterly Trend of Work Intensity Index (2011. Q1 ~ 2022.Q1)

<2015=100)

Quarter	Economy-wide	Primary Ind.	Secondary Ind.	Service Ind.
201114	100.4	108.5	102.6	102.8
201124	104.8	104.1	108.3	105.1
201134	106.8	108.1	109.9	106.8
201144	102.4	113.8	104.3	106.9
201234	98.0	115.5	101.5	98.2
201234	104.1	123.5	105.9	108.1
201234	92.4	117.1	96.8	95.6
201244	97.8	101.1	100.5	101.3
201314	93.9	106.8	97.6	95.4
201324	97.6	103.1	98.0	103.1
201334	95.8	107.0	97.8	101.1
201344	99.0	108.8	100.4	100.9
201414	100.9	108.5	104.1	100.8
201424	107.5	112.8	108.8	106.2
201434	101.5	107.5	102.0	103.9
201444	100.6	104.4	100.5	102.9
201514	101.3	98.1	102.5	99.3
201524	103.8	99.7	102.8	105.3
201534	98.0	101.4	97.9	98.5
201544	97.8	101.0	97.9	97.5
201614	99.5	104.7	99.9	96.9
201624	102.2	105.1	102.0	102.9
201634	98.5	109.4	99.0	99.4
201644	99.7	108.4	99.6	99.7

3. Data and Methodologies

(Table 4) Quarterly Trend of Work Intensity Index (2011. Q1 ~ 2022.Q1)

<2015=100)

Quarter	Economy-wide	Primary Ind.	Secondary Ind.	Service Ind.
201714	93.5	88.4	94.9	94.2
201724	101.3	92.9	102.6	103.3
201734	93.1	91.1	96.6	92.6
201744	99.0	106.9	98.6	105.2
201814	88.4	90.8	89.5	94.5
201824	96.0	99.7	95.1	105.5
201834	91.3	95.8	89.6	103.4
201844	92.7	107.1	90.8	105.5
201914	90.4	105.8	88.9	100.9
201924	89.9	102.6	86.9	101.0
201934	85.4	105.5	82.8	99.4
201944	87.1	105.4	83.4	100.8
202014	82.0	106.8	77.3	96.5
202024	80.7	115.6	74.0	97.8
202034	80.9	115.6	76.7	95.8
202044	87.4	120.8	82.7	102.3
202114	83.7	113.9	79.1	97.5
202124	81.9	120.4	76.9	97.9
202134	81.1	102.7	76.3	98.8
202144	81.3	102.8	75.0	102.2
202214	85.5	105.2	79.8	103.8
202224	83.4	105.8	77.5	102.9

3. Data and Methodologies

(4) Estimates of Quarterly TFP

• Estimates of quarterly TFP from Model 1 (unadjusted TFP), Model 2 (capital- adjusted) and Model 3 (capital-adjusted and labor-adjusted) are presented in Table 5-7, 8-10 and 11-13 respectively. It is noted that TFP growth rates at Economy-wide level are Model 1: 0.70(26.7 %), Model 2: 0.85 (32.4 %) and Model 3: 0.85 (32.4 %).

• The input-utilization adjustments have made the estimated TFP growth rates bigger in both absolute terms and relative contribution.

3. Data and Methodologies

➢ **Model 1(Unadjusted TFP)**

• Model 1 estimates quarterly TFP without adjusting growth rates by input utilization rates. As shown in Table 5, 6 and 7, the economy-wide level of TFP growth rate is the largest during the Pandemic sub-period (2020 1/4-2022 1/4) because of negative growth rate (relative contribution) by labor input during the Pandemic period. It should be noted even during the Pandemic period, the growth rate of TFP in Secondary industry (2.19 %) and Service industry (1.51 %) explains almost all of GDP growth rate helped by positive growth rate of capital input (1.09 % and 0.89 % respectively).

• Estimates of TFP by industry from Model 1(unadjusted TFP) shows a lot of recovery in Manufacturing (Figure 14). Within Service sector, Transportation & Storage, Accommodation & Food and Wholesale & Retail industry's TFP shows greater volatility (Figure 15) and most severely affected sectors from Pandemic as documented in Pyo (2021).

3. Data and Methodologies

(Table 5) Quarterly Growth Accounting Result: Model 1 (2012. Q1 ~ 2022.Q1)

<Growth rate(%), Contribution rate(%)>

	GDP	Labor	Capital	TFP
Economy-wide	2.63	0.67	1.26	0.70
Primary Industry	0.39	0.01	0.16	0.22
Secondary Industry	2.42	0.50	1.66	0.27
Service Industry	2.85	0.81	1.04	1.00
		Contribution		
Economy-wide	100.0	25.5	47.8	26.7
Primary Industry	100.0	2.6	40.5	57.0
Secondary Industry	100.0	20.6	68.3	11.1
Service Industry	100.0	28.3	36.6	35.1

3. Data and Methodologies

(Table 6) Quarterly Growth Accounting Result: Model 1 (2012. Q1 ~ 2019.Q1)

<Growth rate(%), Contribution rate(%)>

	GDP	**Labor**	**Capital**	**TFP**
Economy-wide	2.89	1.03	1.34	0.52
Primary Industry	0.66	-0.52	-0.28	1.47
Secondary Industry	2.59	0.99	1.85	-0.25
Service Industry	3.17	1.19	1.08	0.89
		Contribution		
Economy-wide	100.0	35.6	46.5	17.8
Primary Industry	100.0	-78.8	-41.7	220.5
Secondary Industry	100.0	38.2	71.3	-9.5
Service Industry	100.0	37.6	34.1	28.2

3. Data and Methodologies

(Table 7) Quarterly Growth Accounting Result: Model 1 (2020. Q1 ~ 2022.Q1)

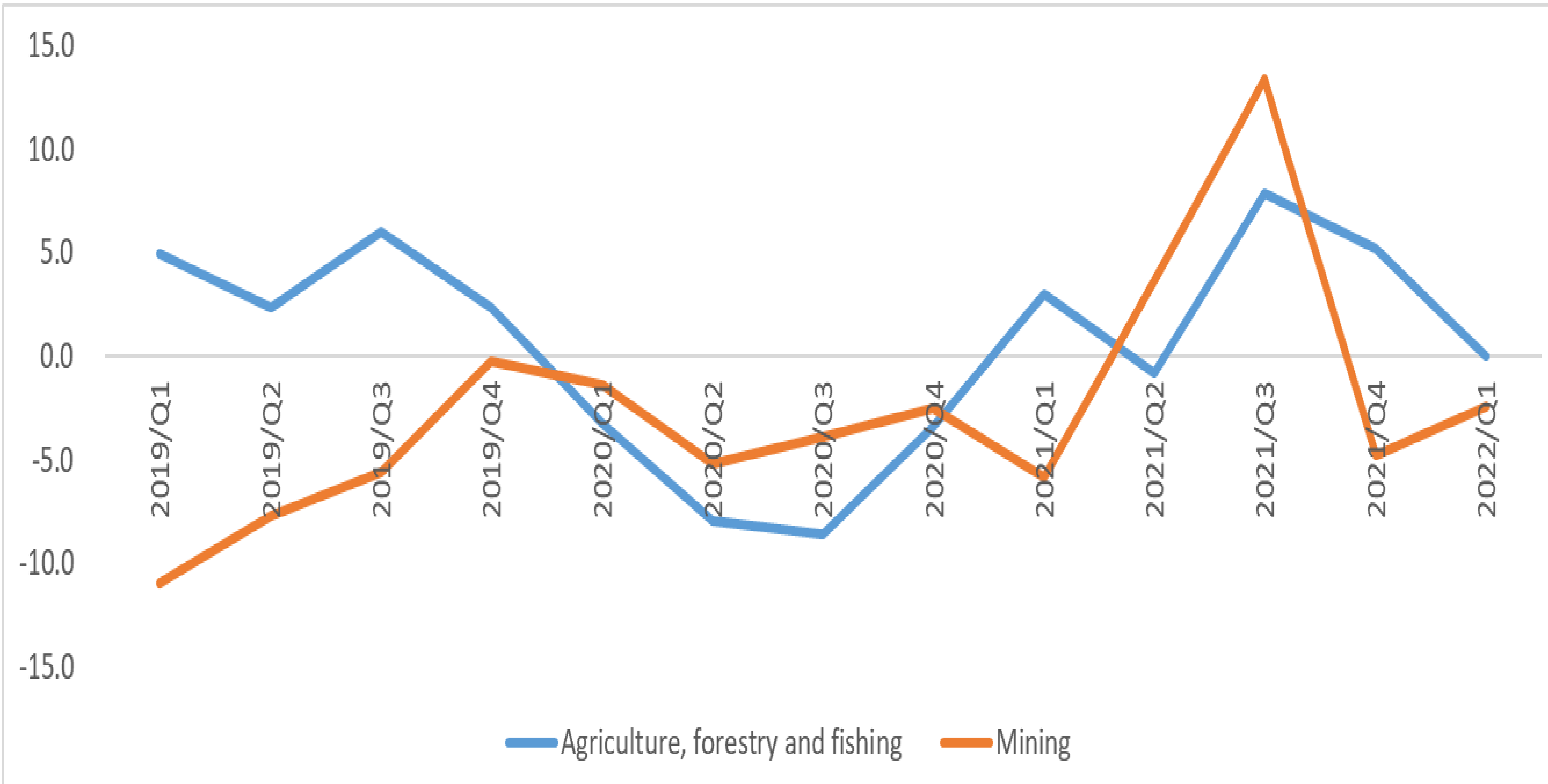
<Growth rate(%), Contribution rate(%)>

	GDP	Labor	Capital	TFP
Economy-wide	1.94	-0.62	0.97	1.59
Primary Industry	-0.89	0.64	1.11	-2.65
Secondary Industry	2.34	-0.94	1.09	2.19
Service Industry	1.81	-0.58	0.89	1.51
		Contribution		
Economy-wide	100.0	-31.8	49.9	81.9
Primary Industry	100.0	-72.0	-124.7	296.7
Secondary Industry	100.0	-40.0	46.6	93.5
Service Industry	100.0	-31.9	48.9	83.0

3. Data and Methodologies

(Figure 13) Estimates of TFP (Model 1, Primary Industry, 2019 Q1 ~ 2022 Q1)

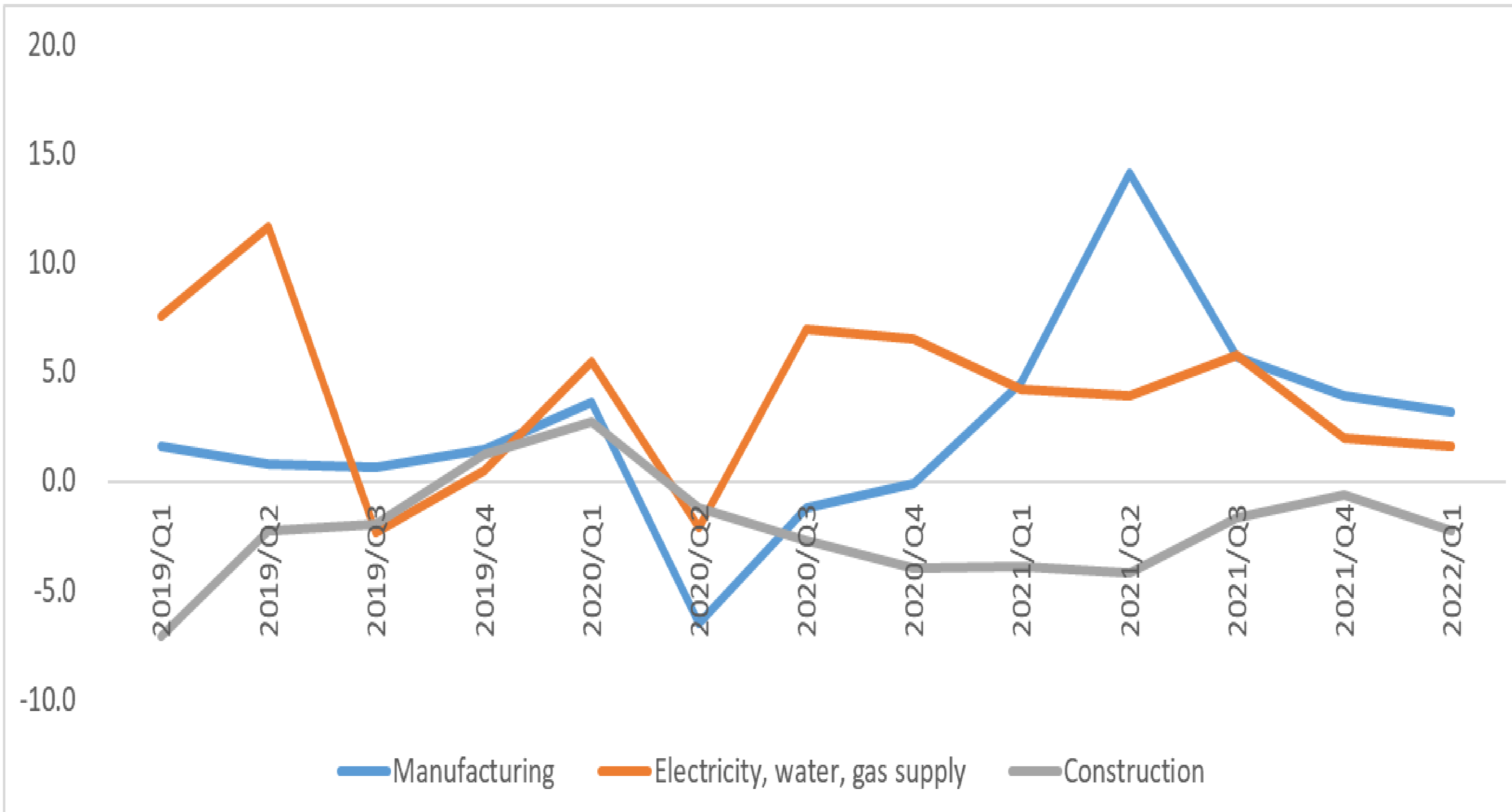
<Growth rate(%)>



3. Data and Methodologies

(Figure 14) Estimates of TFP (Model 1, Secondary Industry, 2019 Q1 ~ 2022 Q1)

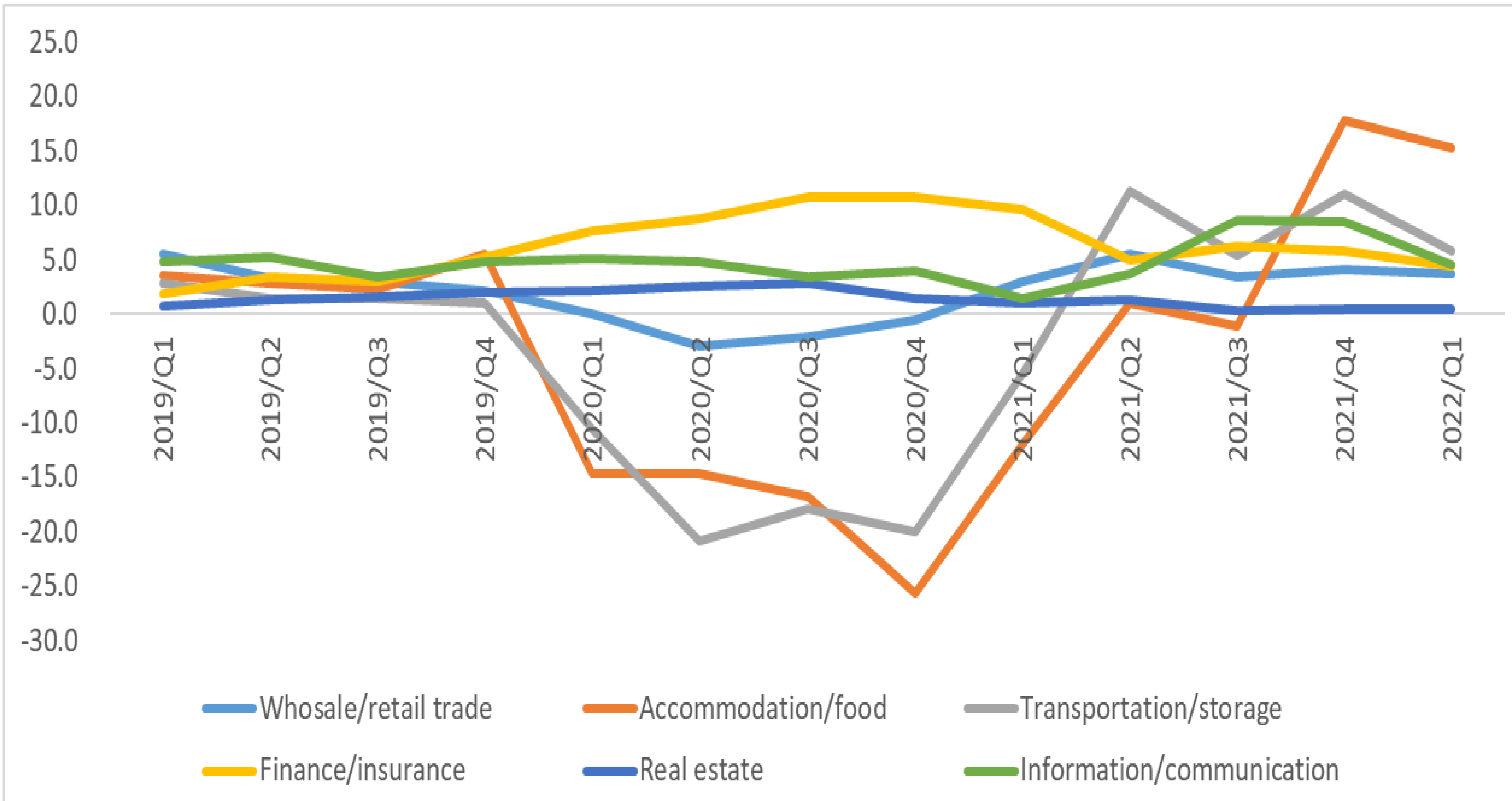
<Growth rate(%)>



3. Data and Methodologies

(Figure 15) Estimates of TFP (Model 1, Service Industry, 2019 Q1 ~ 2022 Q1)

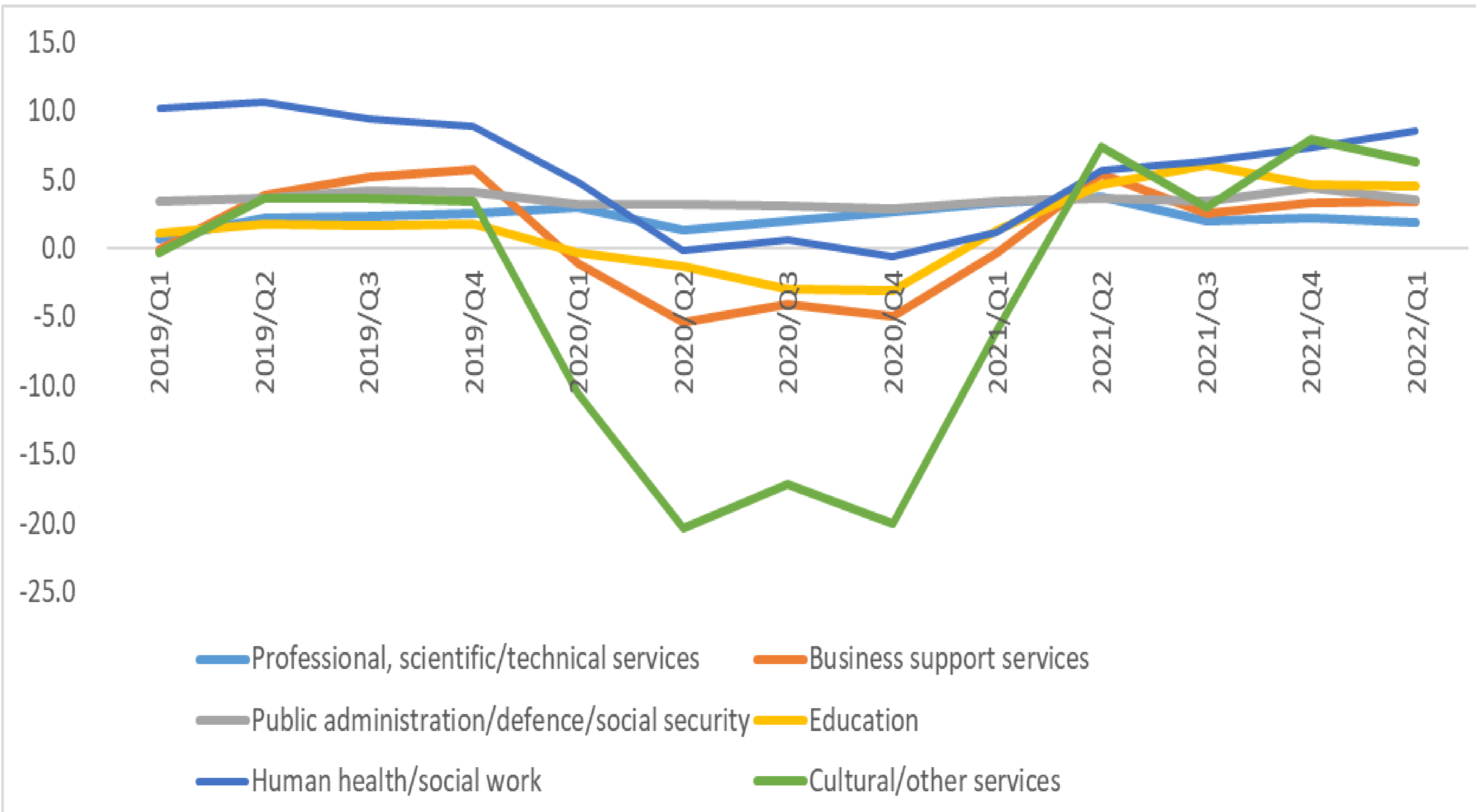
<Growth rate(%)>



3. Data and Methodologies

(Figure 15) Estimates of TFP (Model 1, Service Industry, 2019 Q1 ~ 2022 Q1, Cont.)

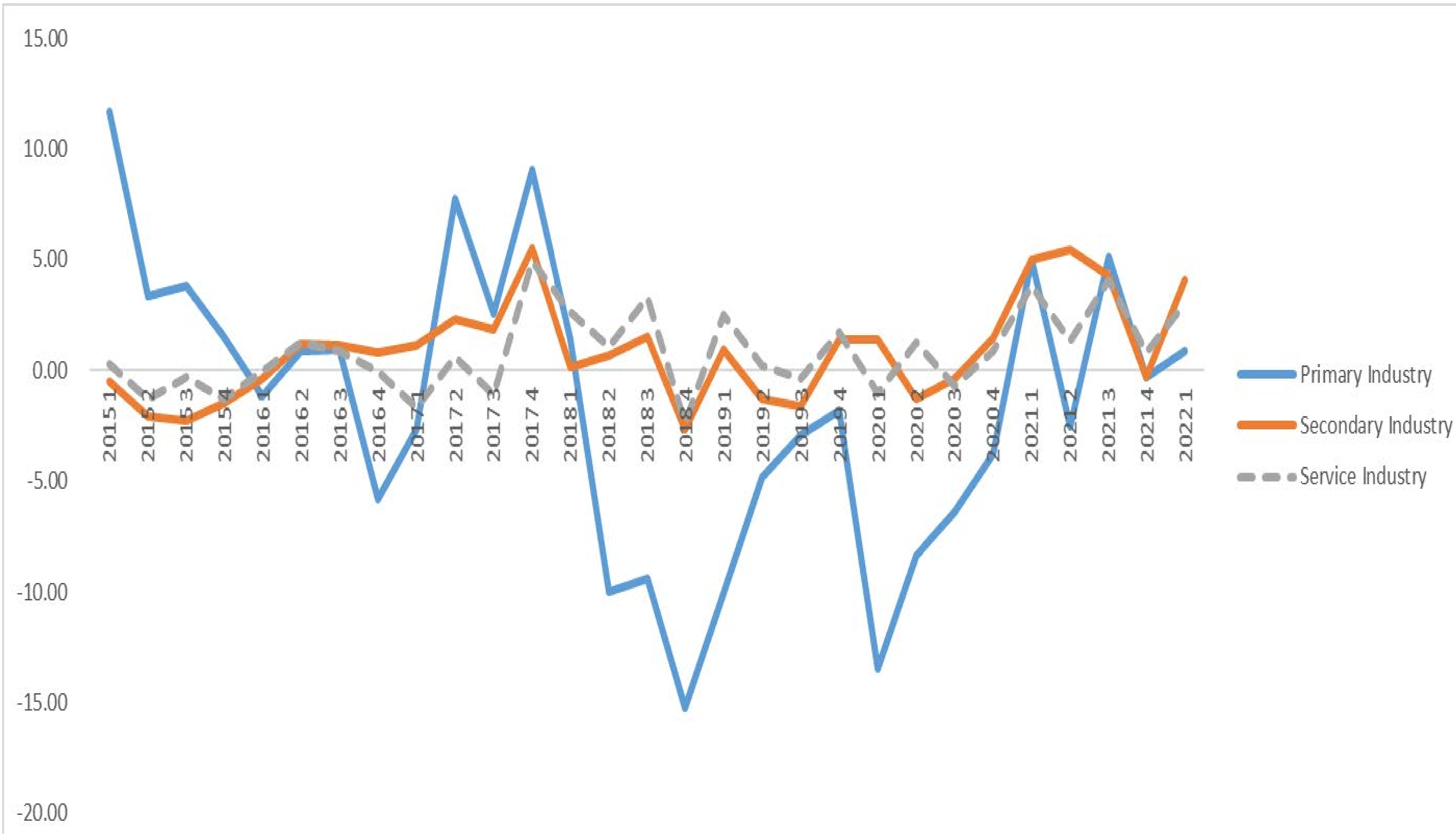
<Growth rate(%)>



3. Data and Methodologies

(Figure 16) Estimates of TFP by Industry, 2015 Q1 ~ 2022 Q1)

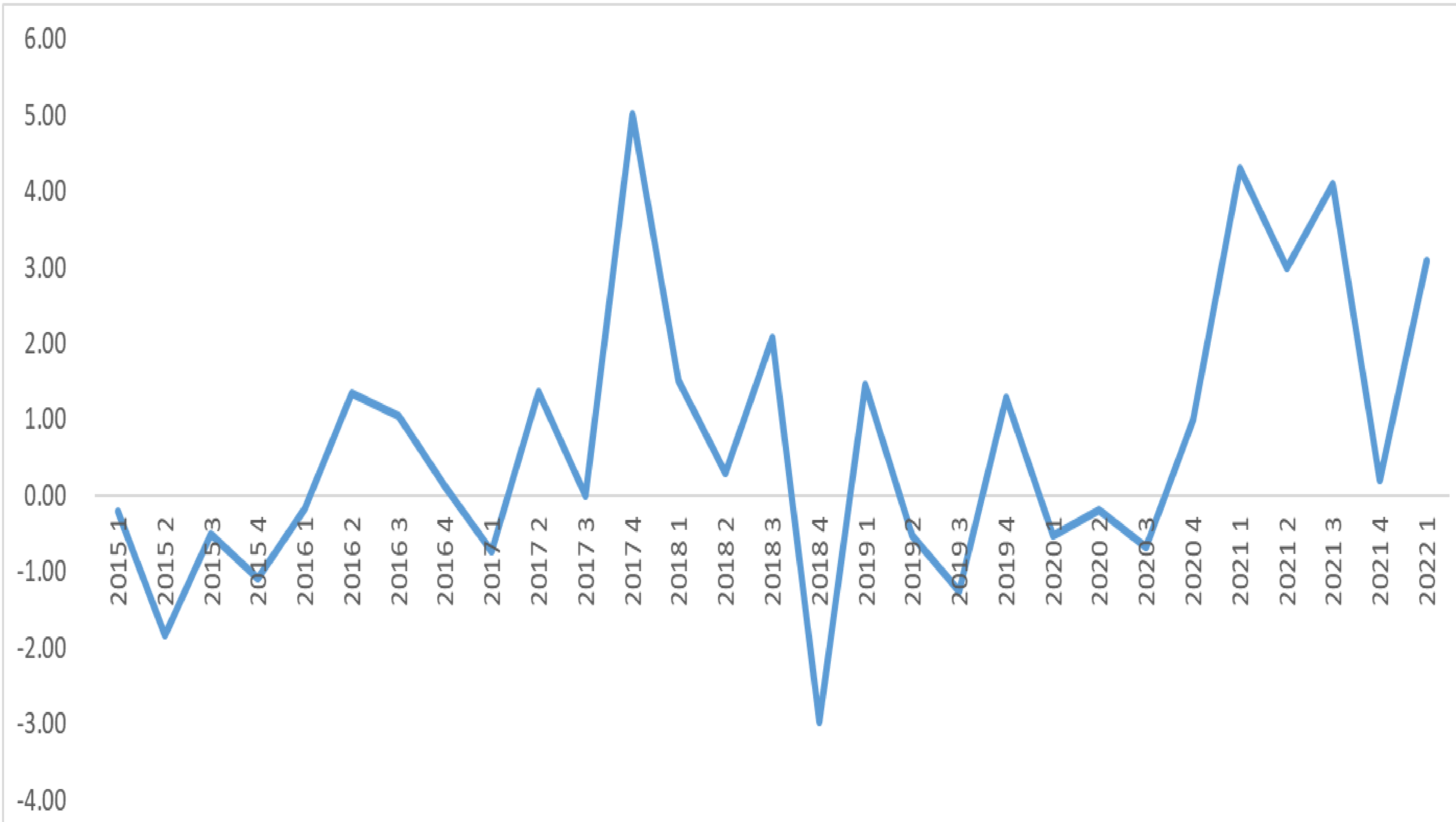
<Growth rate(%)>



3. Data and Methodologies

(Figure 17) Estimates of TFP for Economy-wide, 2015 Q1 ~ 2022 Q1)

<Growth rate(%)>



3. Data and Methodologies

➢ **Model 2(Capital-adjusted TFP)**

• Model 2 adjusts capital input using capacity utilization ratio index from Statistics Korea for Manufacturing sector and the utilization index using Electric Power Usage in all other Non- Manufacturing industries by using Energy Statistics by Korea Energy Economics Institute following Pyo and Song (2014).

• Quarterly estimates of TFP growth rates for the entire period in Table 8 shows the fastest growth in Service industry (0.94 %) with a significant relative contribution (33.1 %). On the other hand, during the Pandemic period, capital–adjusted TFP growth rate in Table 10 is the largest in Manufacturing (2.22 %) with dominant relative contribution to GDP (94.8 %). It implies during the Pandemic-period Secondary industry including Manufacturing has managed to record 2.34 % GDP growth rate and a 1.06 % growth rate of capital input after being adjusted by capacity utilization rate.

3. Data and Methodologies

(Table 8) Quarterly Growth Accounting Result: Model 2 (2012. Q1 ~ 2022.Q1)

<Growth rate(%), Contribution rate(%)>

	GDP	Labor	Capital	TFP
Economy-wide	2.63	0.67	1.11	0.85
Primary Industry	0.39	0.01	-0.18	0.56
Secondary Industry	2.42	0.50	1.33	0.59
Service Industry	2.85	0.81	1.10	0.94
		Contribution		
Economy-wide	100.0	25.5	42.1	32.4
Primary Industry	100.0	2.6	-46.1	143.5
Secondary Industry	100.0	20.6	54.8	24.5
Service Industry	100.0	28.3	38.6	33.1

3. Data and Methodologies

(Table 9) Quarterly Growth Accounting Result: Model 2 (2012. Q1 ~ 2019.Q1)

<Growth rate(%), Contribution rate(%)>

	GDP	Labor	Capital	TFP
Economy-wide	2.89	1.03	1.08	0.78
Primary Industry	0.66	-0.52	-0.79	1.97
Secondary Industry	2.59	0.99	1.41	0.19
Service Industry	3.17	1.19	1.12	0.85
		Contribution		
Economy-wide	100.0	35.6	37.3	27.1
Primary Industry	100.0	-78.8	-118.4	297.2
Secondary Industry	100.0	38.2	54.5	7.3
Service Industry	100.0	37.6	35.5	26.9

3. Data and Methodologies

(Table 10) Quarterly Growth Accounting Result: Model 2 (2020. Q1 ~ 2022.Q1)

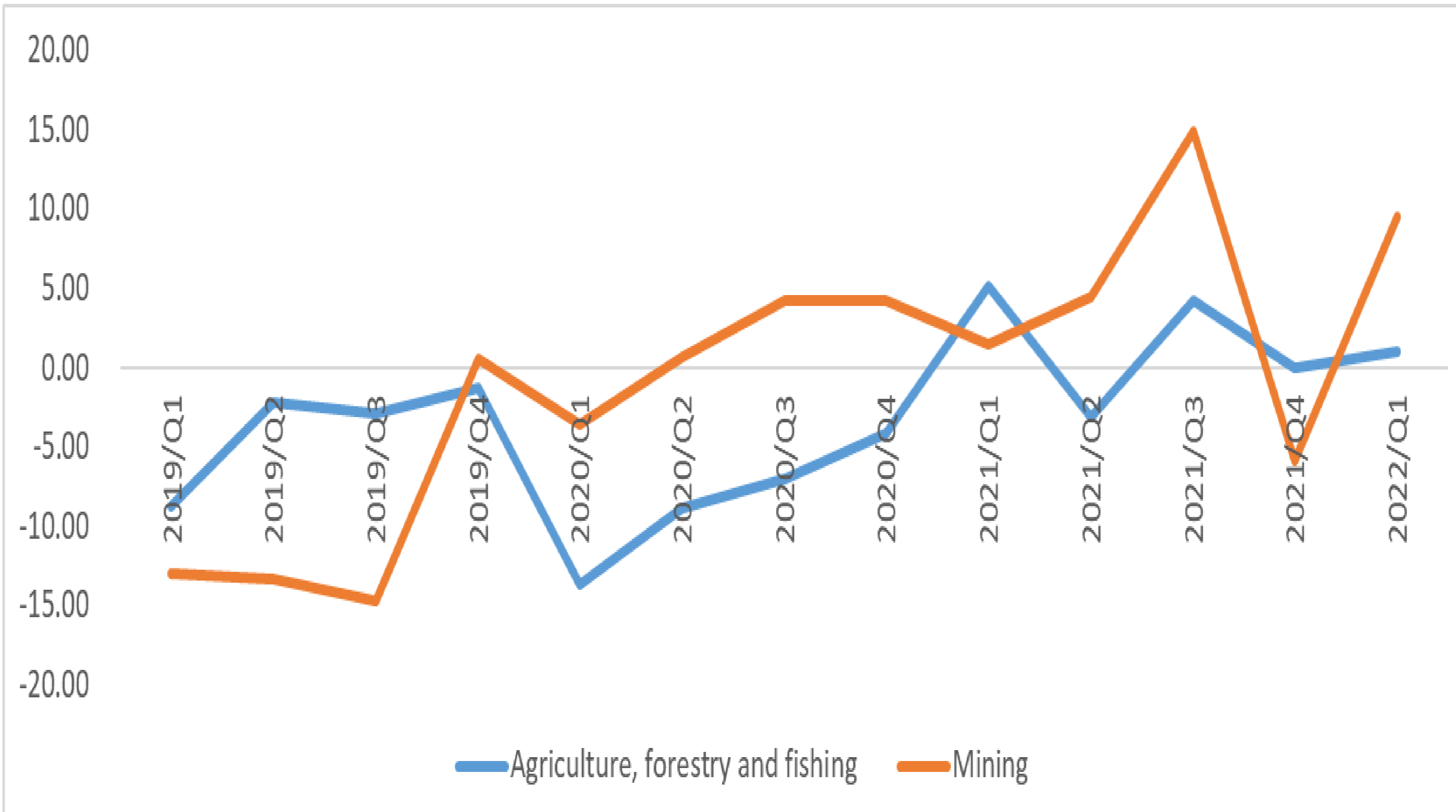
<Growth rate(%), Contribution rate(%)>

	GDP	Labor	Capital	TFP
Economy-wide	1.94	-0.62	1.09	1.47
Primary Industry	-0.89	0.64	1.23	-2.76
Secondary Industry	2.34	-0.94	1.06	2.22
Service Industry	1.81	-0.58	0.97	1.42
		Contribution		
Economy-wide	100.0	-31.8	55.9	75.9
Primary Industry	100.0	-72.0	-138.1	310.1
Secondary Industry	100.0	-40.0	45.2	94.8
Service Industry	100.0	-31.9	53.4	78.5

3. Data and Methodologies

(Figure 18) Estimates of TFP (Model 2, Primary Industry, 2019 Q1 ~ 2022 Q1)

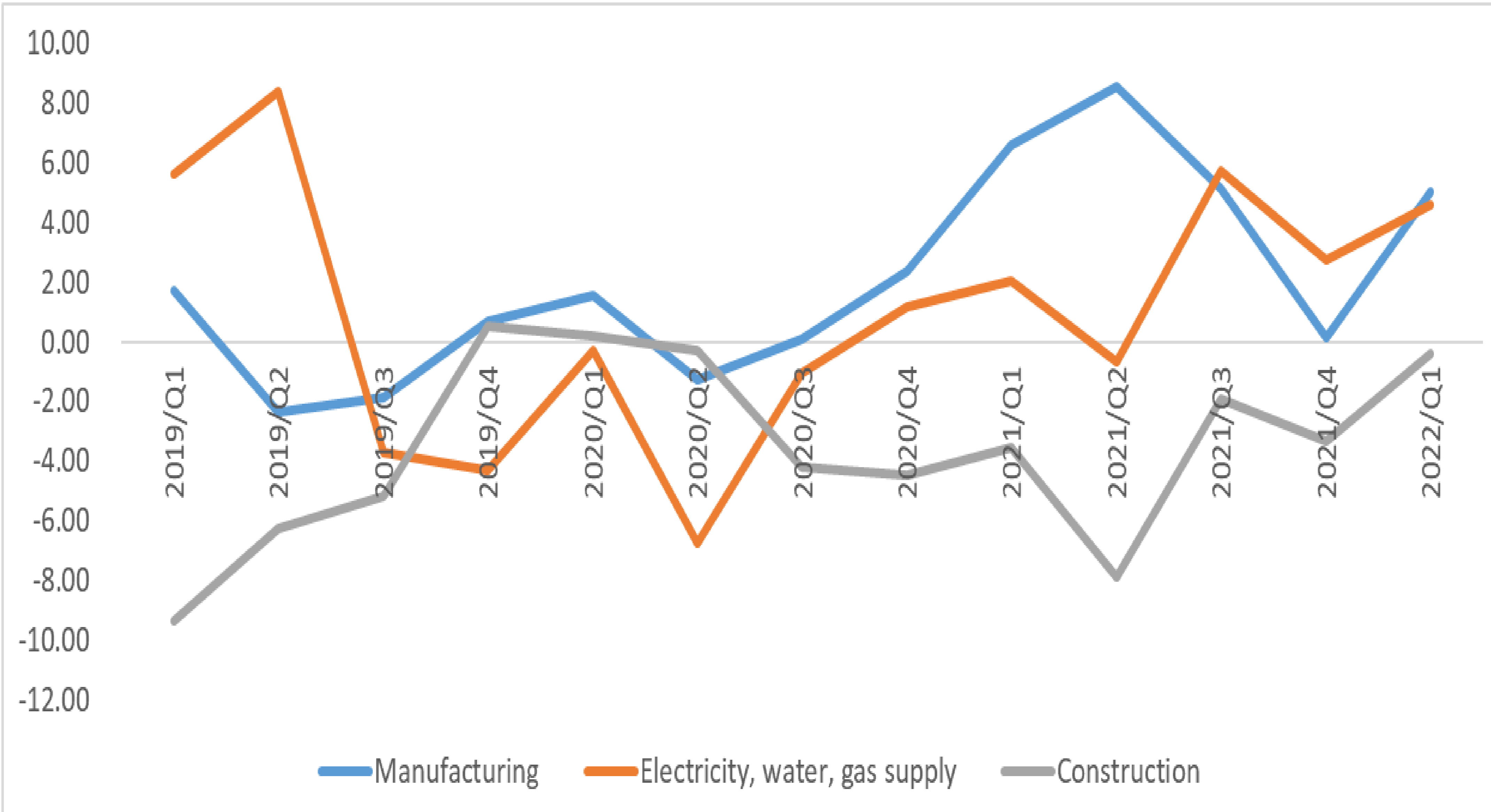
<Growth rate(%)>



3. Data and Methodologies

(Figure 19) Estimates of TFP (Model 2, Secondary Industry, 2019 Q1 ~ 2022 Q1)

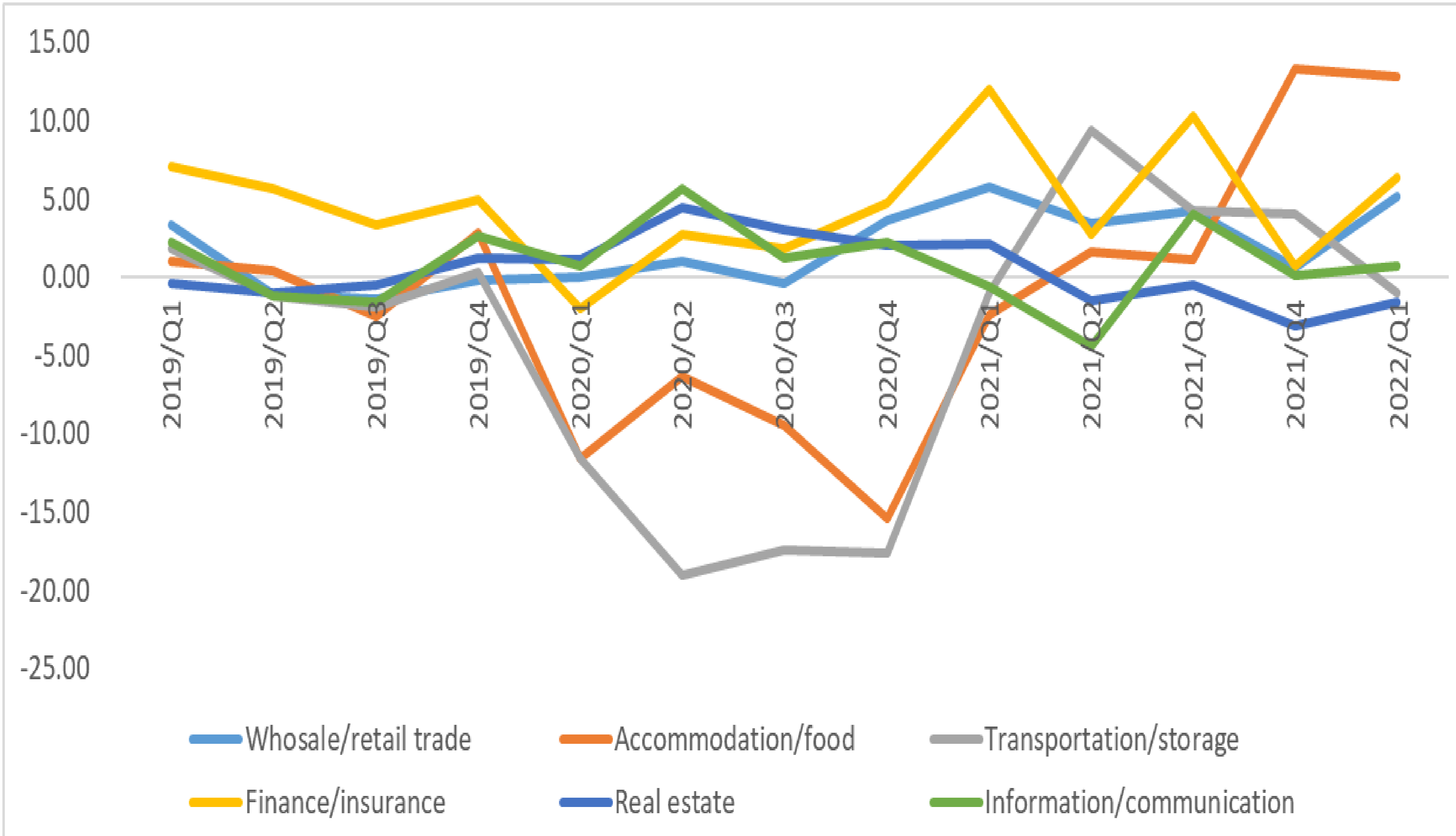
<Growth rate(%)>



3. Data and Methodologies

(Figure 20) Estimates of TFP (Model 2, Service Industry, 2019 Q1 ~ 2022 Q1)

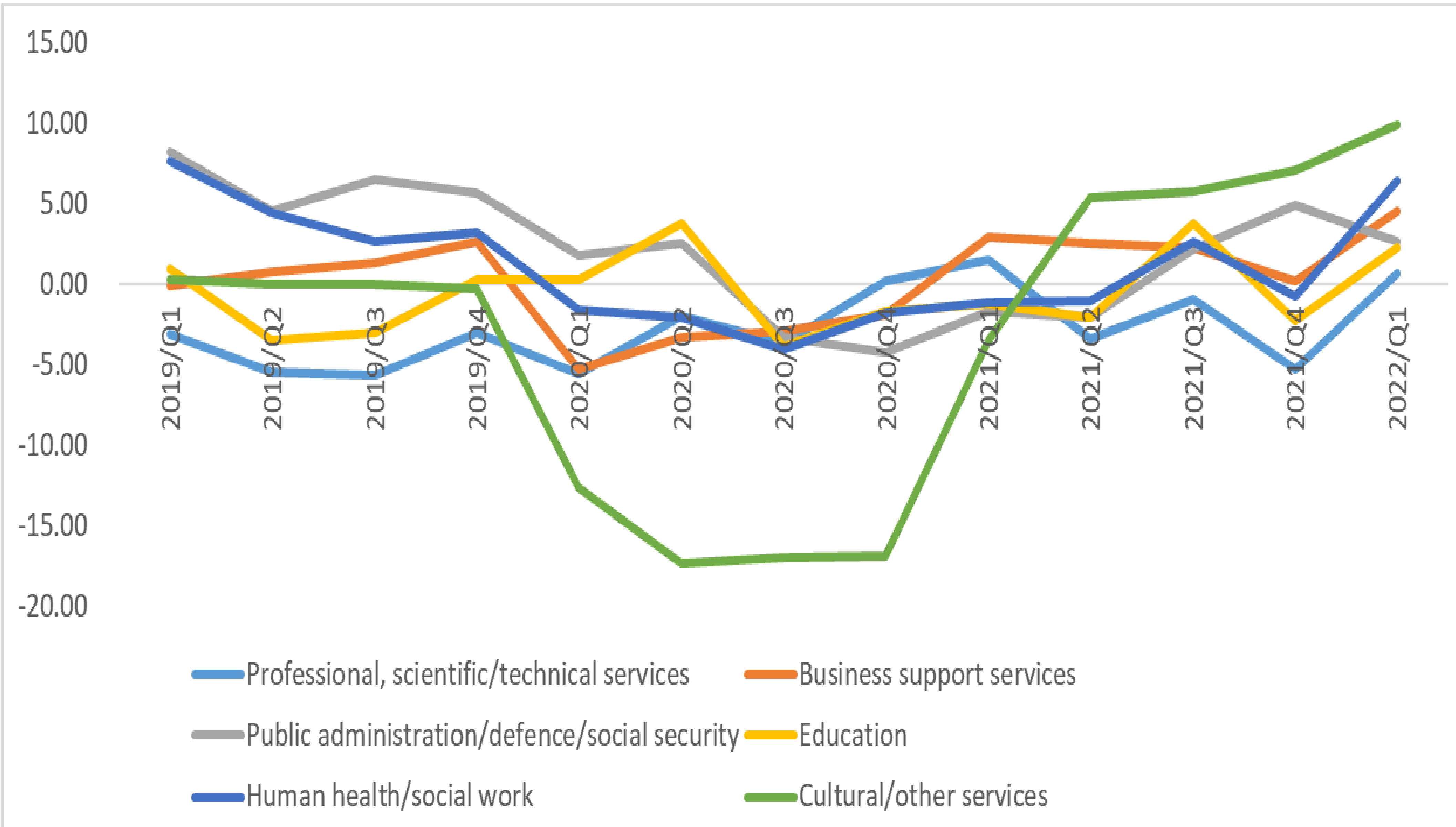
<Growth rate(%)>



3. Data and Methodologies

(Figure 20) Estimates of TFP (Model 2, Service Industry, 2019 Q1 ~ 2022 Q1, Cont.)

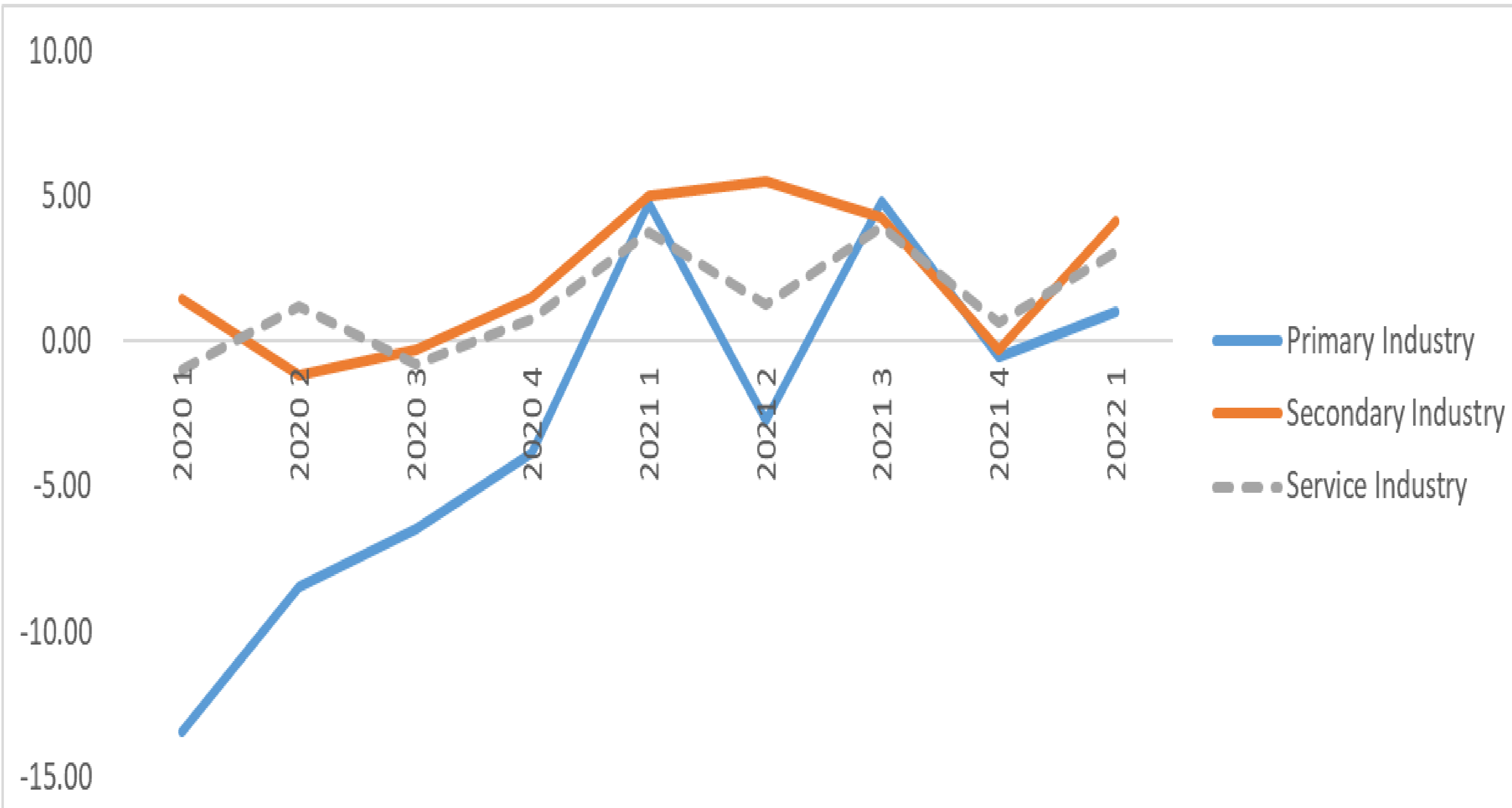
<Growth rate(%)>



3. Data and Methodologies

(Figure 21) Estimates of TFP by Industry(Model 2, 2020 Q1 ~ 2022 Q1, Cont.)

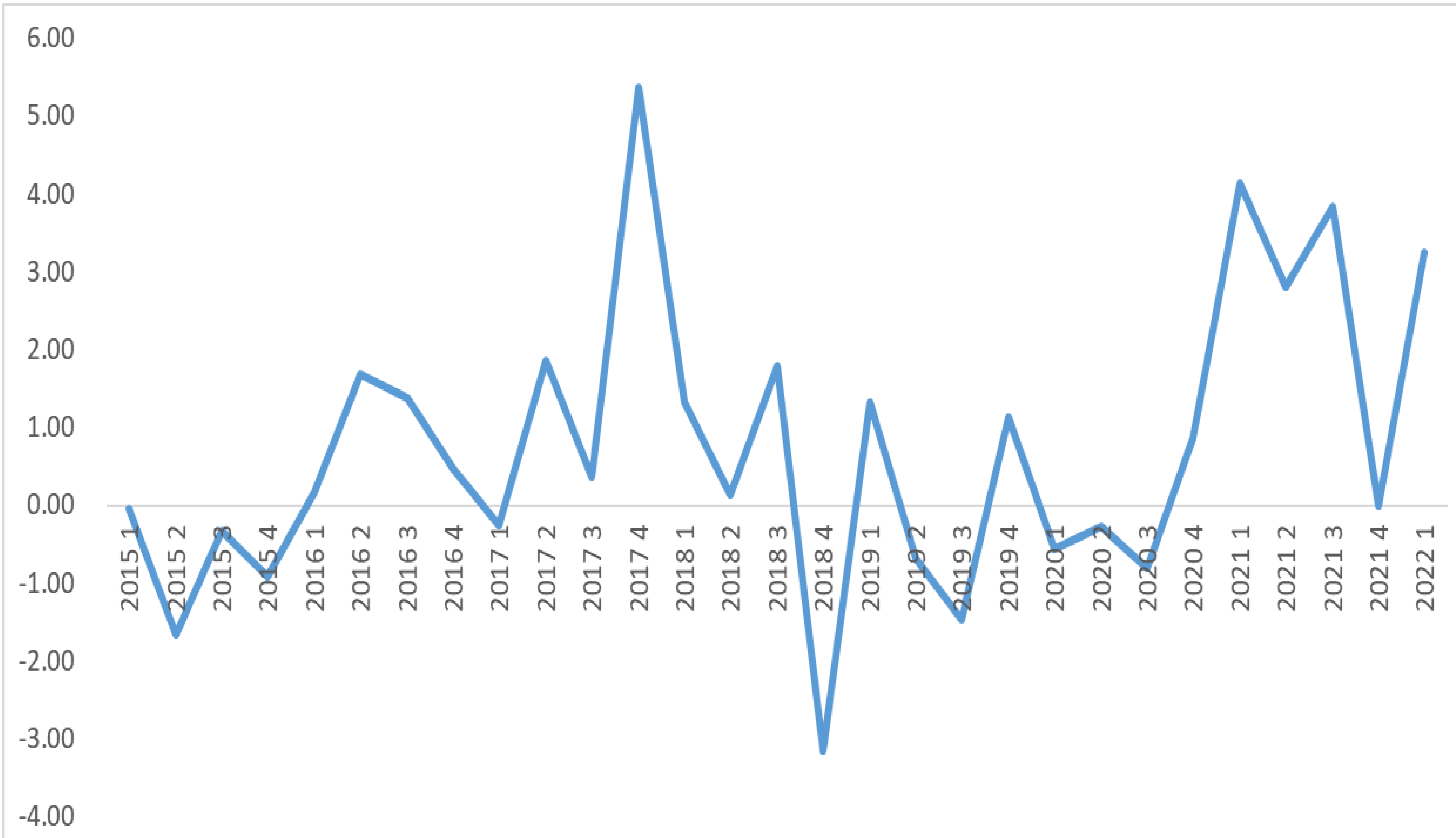
<Growth rate(%)>



3. Data and Methodologies

(Figure 22) Estimates of TFP for Economy-wide(Model 2, 2015 Q1 ~ 2022 Q1)

<Growth rate(%)>



3. Data and Methodologies

➢ **Model 3(Capital and Labor-adjusted TFP)**

• The last model of quarterly growth accounting adjusts TFP by both capacity utilization index and labor-intensity index. For the entire period of estimation (2012 1/4 – 2022 1/4), the growth rate of TFP is the largest in Service sector (0.94 %) with relative contribution (33.0 %) as shown in Table 11.

• It should be noted that as shown in Figure 12 during the Pandemic period the work intensity index of the Secondary sector did not increase but rather got reduced implying that there was not massive lay-offs. Therefore, the labor input during the Pandemic period was not adjusted much by work-intensity index maintaining the similar growth rate of TFP from Model 2 (2.22 %)

3. Data and Methodologies

(Table 11) Quarterly Growth Accounting Result: Model 3 (2012. Q1 ~ 2022.Q1)

<Growth rate(%), Contribution rate(%)>

	GDP	Labor	Capital	TFP
Economy-wide	2.63	0.67	1.11	0.85
Primary Industry	0.39	-0.13	-0.18	0.70
Secondary Industry	2.42	0.51	1.33	0.59
Service Industry	2.85	0.81	1.10	0.94
		Contribution		
Economy-wide	100.0	25.5	42.1	32.4
Primary Industry	100.0	-34.1	-46.1	180.2
Secondary Industry	100.0	21.0	54.8	24.2
Service Industry	100.0	28.4	38.6	33.0

3. Data and Methodologies

(Table 12) Quarterly Growth Accounting Result: Model 3 (2012. Q1 ~ 2019.Q1)

<Growth rate(%), Contribution rate(%)>

	GDP	Labor	Capital	TFP
Economy-wide	2.89	1.02	1.08	0.79
Primary Industry	0.66	-0.64	-0.79	2.09
Secondary Industry	2.59	1.05	1.41	0.13
Service Industry	3.17	1.18	1.12	0.86
		Contribution		
Economy-wide	100.0	35.4	37.3	27.3
Primary Industry	100.0	-96.5	-118.4	314.9
Secondary Industry	100.0	40.6	54.5	4.9
Service Industry	100.0	37.2	35.5	27.3

3. Data and Methodologies

(Table 13) Quarterly Growth Accounting Result: Model 3 (2020. Q1 ~ 2022.Q1)

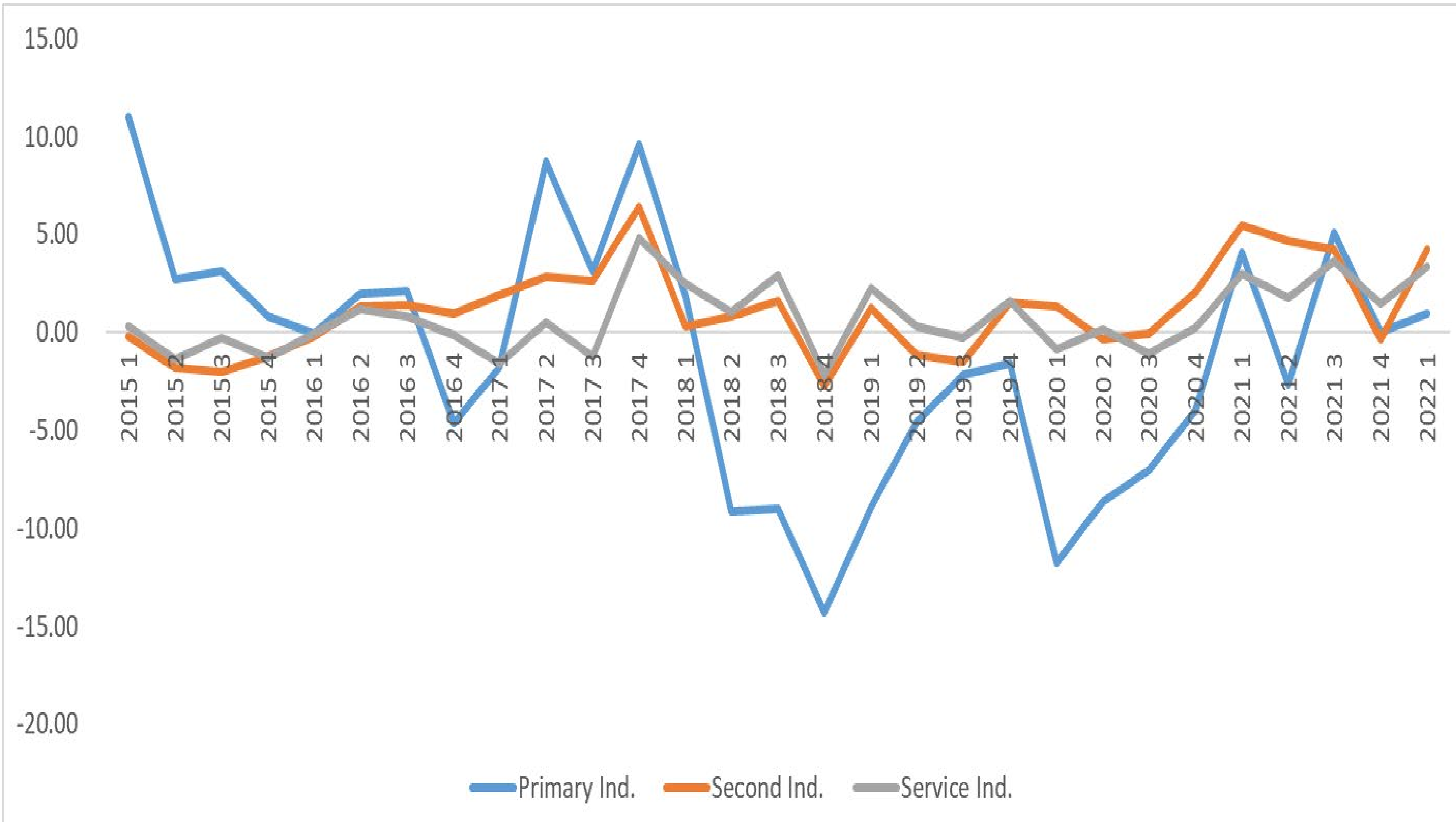
<Growth rate(%), Contribution rate(%)>

	GDP	Labor	Capital	TFP
Economy-wide	1.94	-0.60	1.09	1.45
Primary Industry	-0.89	0.51	1.23	-2.63
Secondary Industry	2.34	-1.09	1.06	2.38
Service Industry	1.81	-0.46	0.97	1.31
		Contribution		
Economy-wide	100.0	-30.6	55.9	74.7
Primary Industry	100.0	-57.2	-138.1	295.3
Secondary Industry	100.0	-46.6	45.2	101.4
Service Industry	100.0	-25.6	53.4	72.2

3. Data and Methodologies

(Figure 23) Estimates of TFP (Model 3, Primary Industry, 2015 Q1 ~ 2022 Q1)

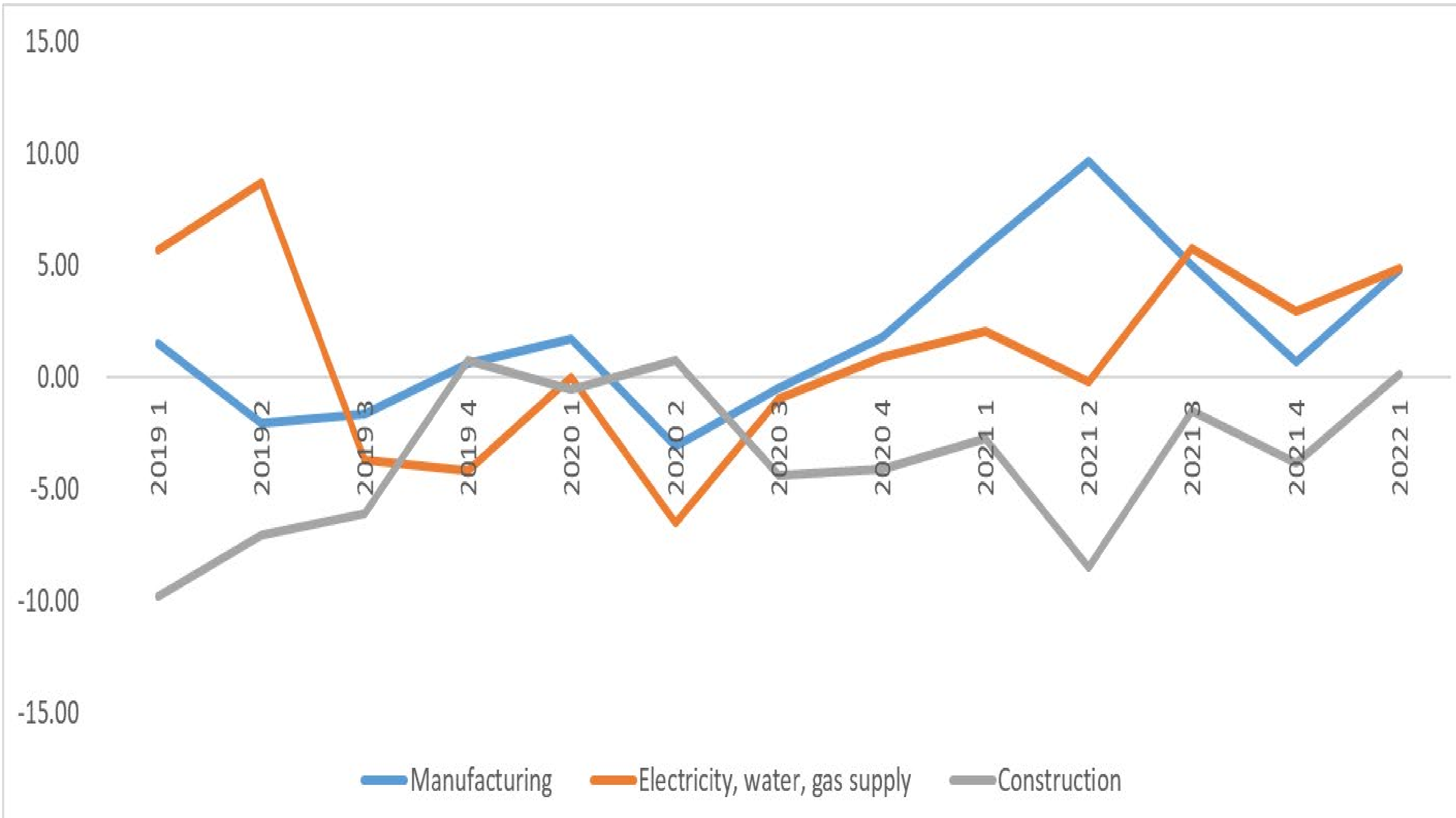
<Growth rate(%)>



3. Data and Methodologies

(Figure 24) Estimates of TFP (Model 3, Secondary Industry, 2019 Q1 ~ 2022 Q1)

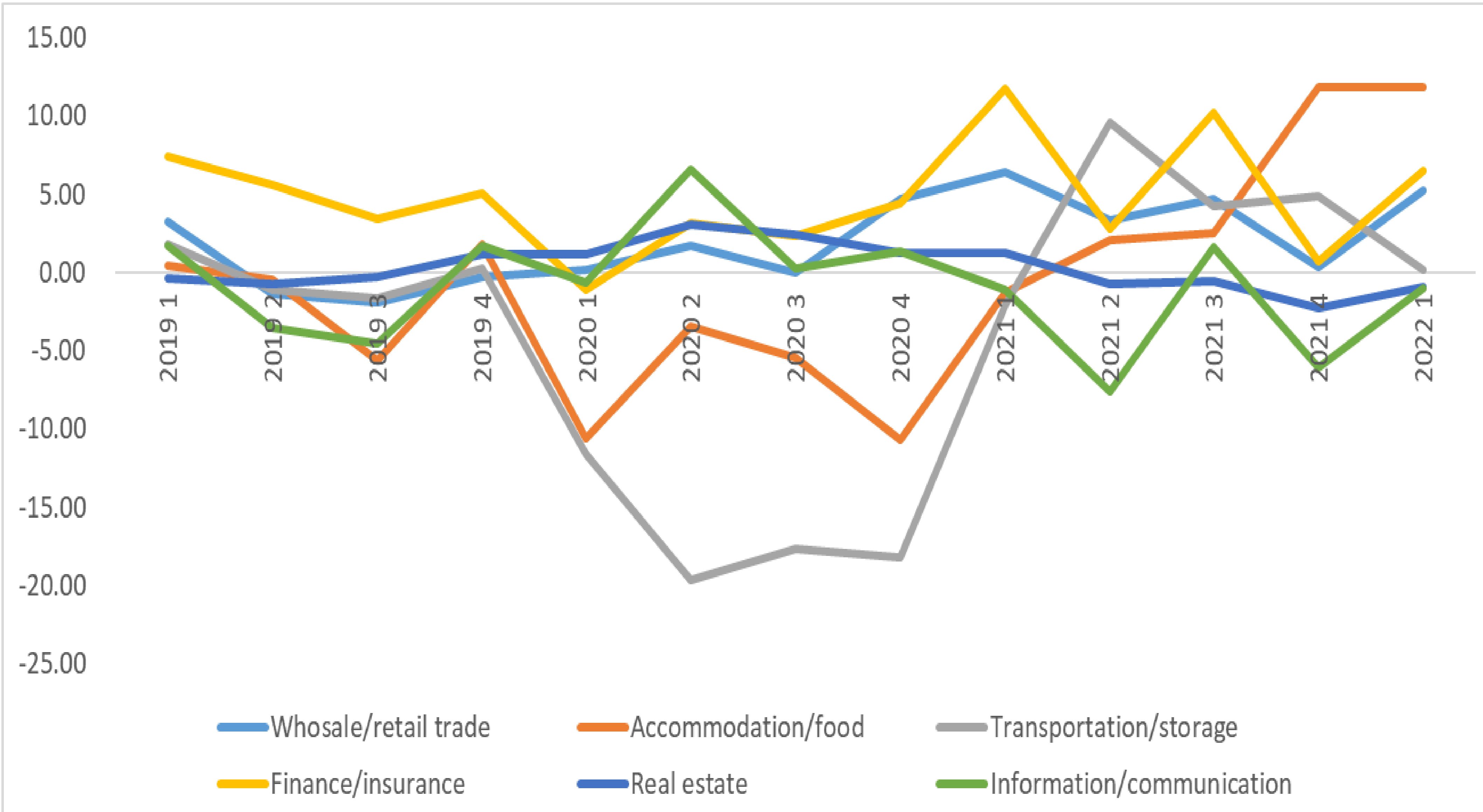
<Growth rate(%)>



3. Data and Methodologies

(Figure 25) Estimates of TFP (Model 3, Service Industry, 2019 Q1 ~ 2022 Q1)

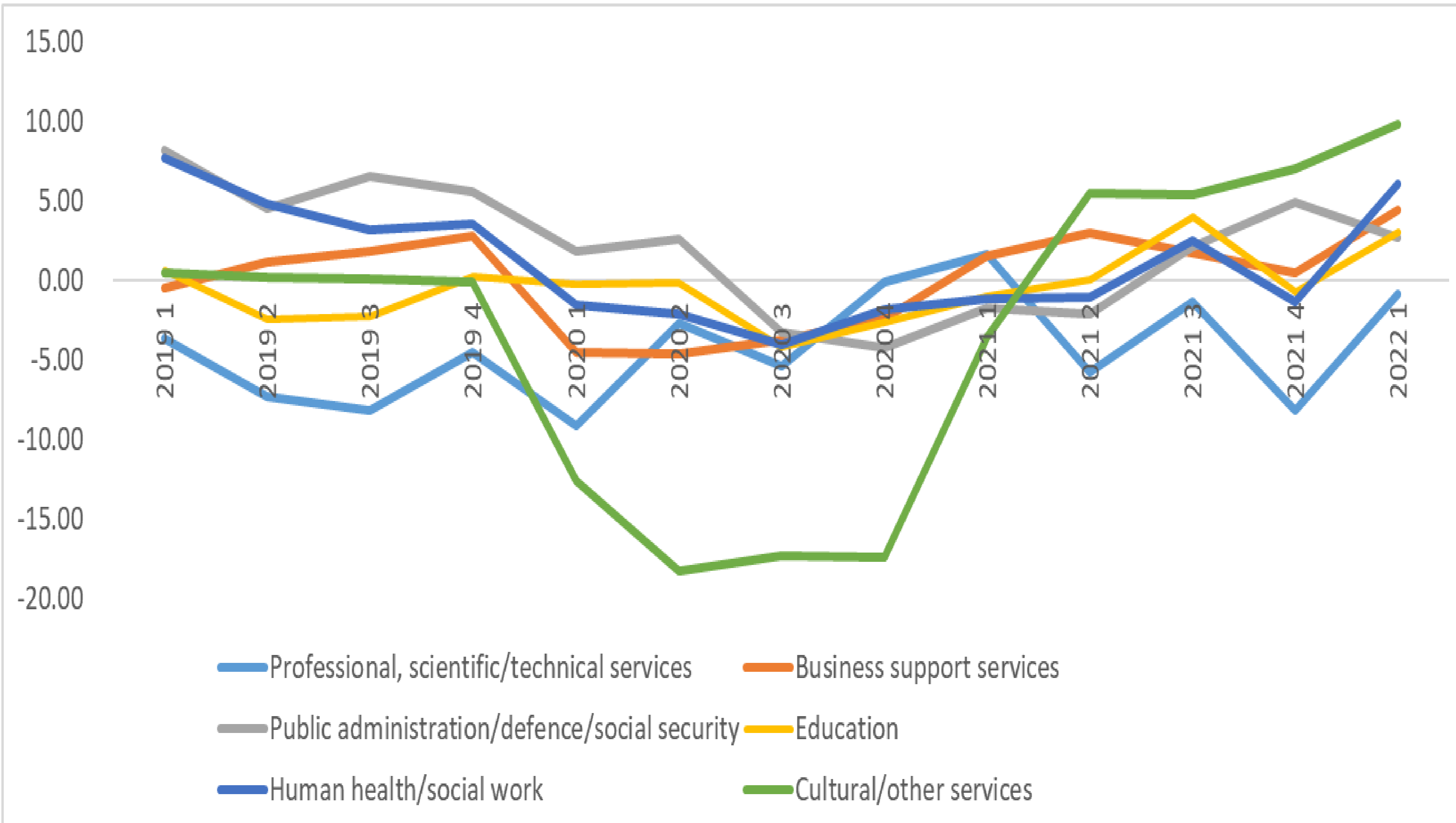
<Growth rate(%)>



3. Data and Methodologies

(Figure 25) Estimates of TFP (Model 3, Service Industry, 2019 Q1 ~ 2022 Q1, cont.)

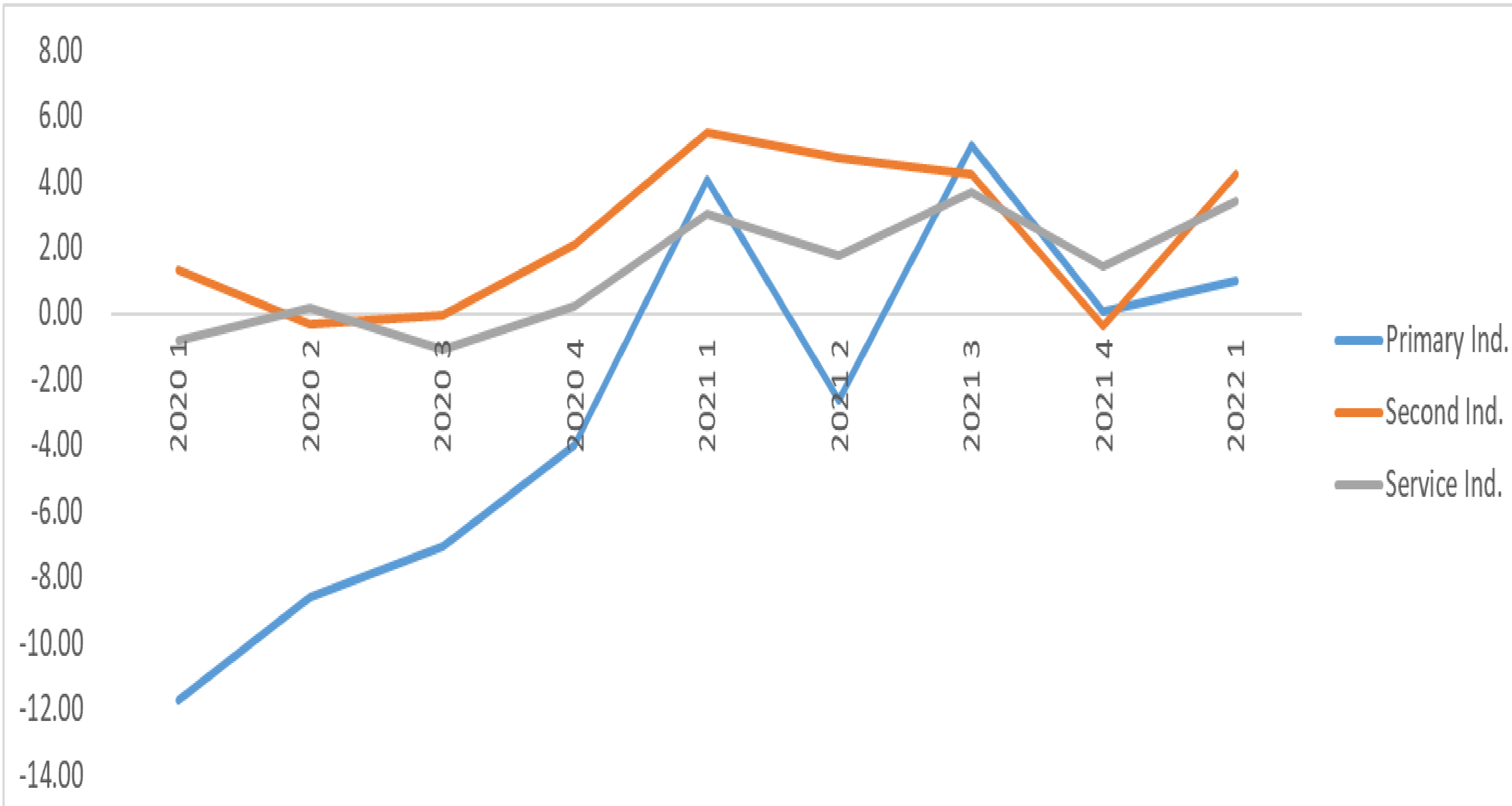
<Growth rate(%)>



3. Data and Methodologies

(Figure 26) Estimates of TFP by Industry (Model 3, 2020 Q1 ~ 2022 Q1)

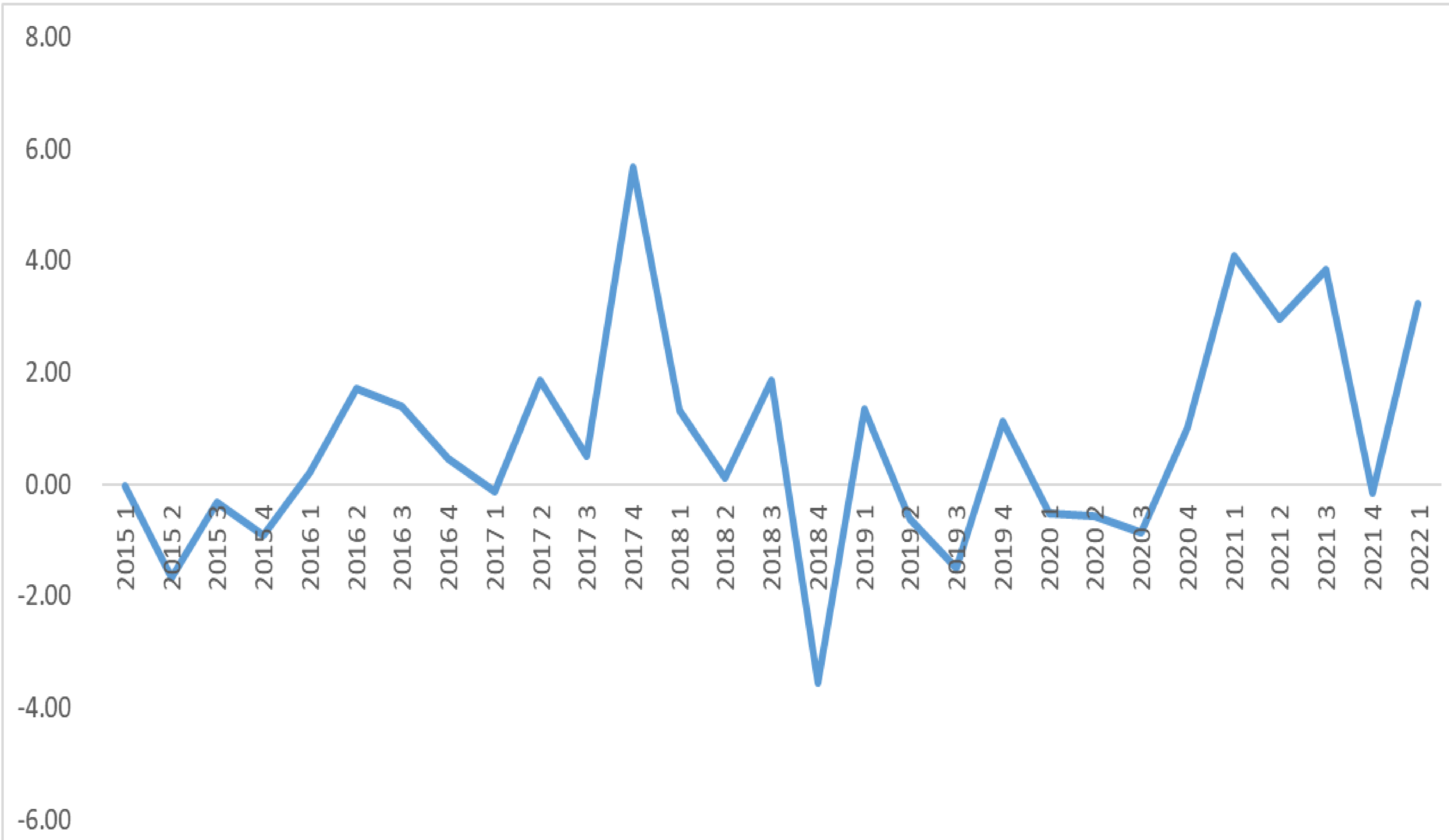
<Growth rate(%)>



3. Data and Methodologies

(Figure 27) Estimates of TFP for Economy-wide(Model 3, 2015 Q1 ~ 2022 Q1)

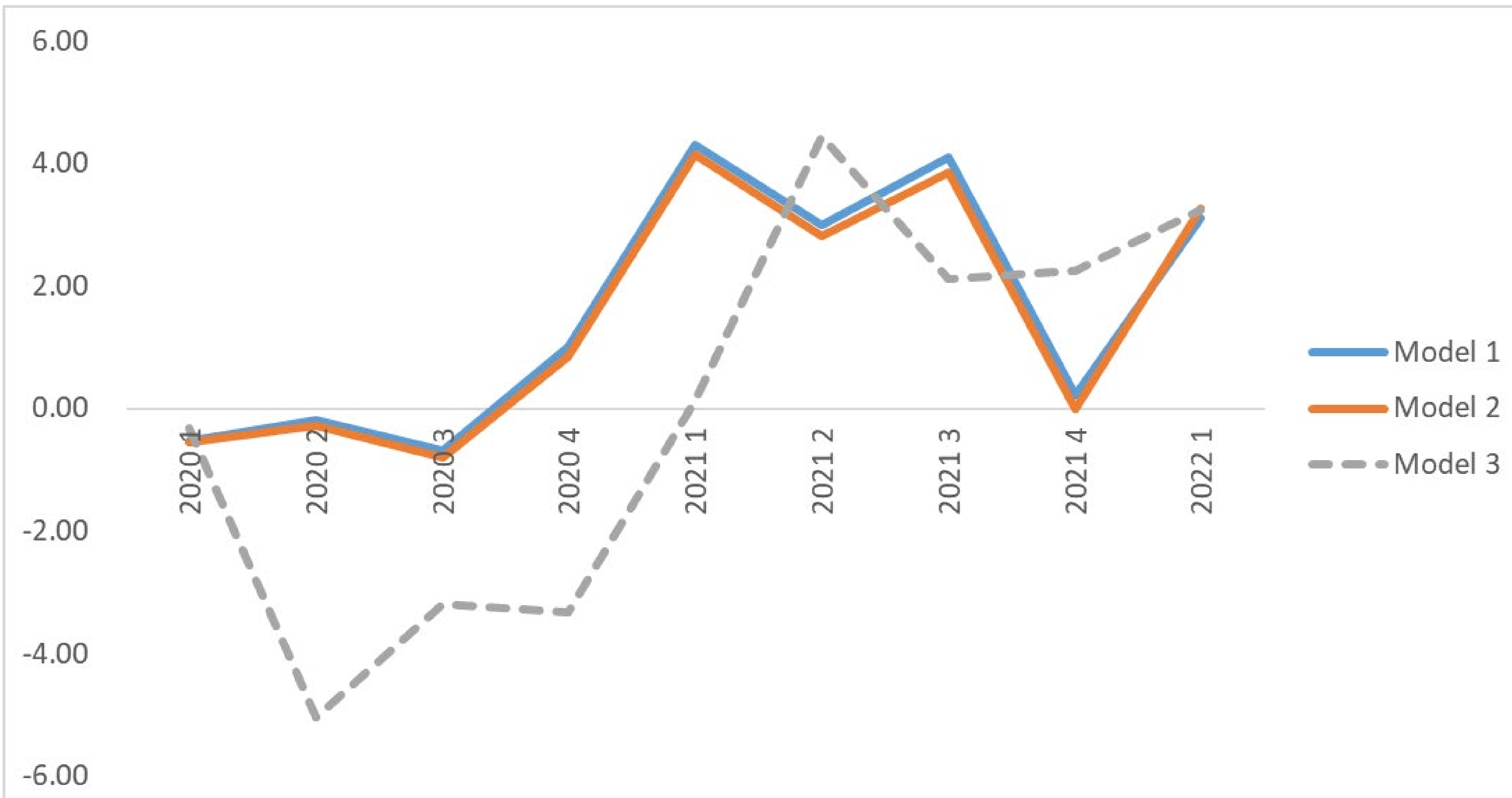
<Growth rate(%)>



3. Data and Methodologies

(Figure 28) TFP Comparison: Model 1, Model 2, and Model 3
(Economy-wide, 2020 Q1 ~ 2022 Q1)

<Growth rate(%)>



3. Data and Methodologies

➢ **Summary**

- In summary, the estimated quarterly TFP series at Economy-wide level are shown in Figure 28. The unadjusted series from Model 1 and the capital utilization-adjusted series from Model 2 are quite similar. They moved downturn at the first quarter of 2020 when the Covid-19 Pandemic broke out. It went down again after the recovery during the period from second quarter of 2020 to the third quarter of 2021. But it declined sharply in the fourth quarter of 2021 during the resurgence of Omicron to be followed by a sharp recovery during the first quarter of 2022. Therefore, we can verify that TFP movements are very pro-cyclical with the Pandemic cycle.

4. Regression of Labor Productivity on Capital Intensity

(1) Model 1

$$\boldsymbol{lnY = \alpha + \beta lnK/L + \epsilon}$$

Y = value-added, L =Labor input, ϵ =stochastic disturbance term

- The regression result shows that estimated share of capital input is the greatest in Service industry (0.80) followed by Primary industry (0.52) and Manufacturing (0.48).

(2) Model 2

$$\boldsymbol{lnY = \alpha + \beta lnK/L + \mathrm{time} + \epsilon}$$

Y= value-added, L =Labor input, time=time trend
ϵ = stochastic disturbance term

- The regression with Time index estimates the growth rate of a neutral technical progress or TFP. The estimates are Primary (0.1 %), Manufacturing (0.1 %) and Service (0.2 %).

4. Regression of Labor Productivity on Capital Intensity

(3) Model 3

$$lnY = \alpha + \beta lnK/L + dum + \epsilon$$

Y = value-added, L =Labor input,
dum=dummy variable
(dum=0 (2011.1 ~ 2019.4), dum=1 (2020.1 ~ 2022.1)
ϵ = stochastic disturbance term

- The regression result with Time Dummy Variable for the Covid-19 period (First quarter of 2020 – First Quarter of 2022) shows negative signs in Primary and Service industry while the signs of Manufacturing coefficient are positive implying that labor productivity in Manufacturing improved during the pandemic period.

4. Regression of Labor Productivity on Capital Intensity

(Table 14) Regression of labor productivity on capital intensity by Industry
(without time index, 2011.1 – 2022.1)

	Economy-wide		**Manufacturing**		**Service**		**Primary Ind.**	
	Model_1	Model_2 (s.a.)	Model_1	Model_2 (s.a.)	Model_1	Model_2 (s.a.)	Model_1	Model_2 (s.a.)
ln(K/L)	0.57***	0.59***	0.47***	0.48***	0.80***	0.82***	0.52***	0.53***
se	-0.044	-0.025	-0.04	-0.032	-0.046	-0.036	-0.089	-0.049
_cons	-2.35***	-2.37***	-2.23***	-2.24***	-2.54***	-2.55***	-2.49***	-2.55***
se	-0.015	-0.009	-0.033	-0.027	-0.009	-0.007	-0.104	-0.057
Adj. R^2	0.79	0.93	0.76	0.84	0.87	0.92	0.44	0.73
Obs.	45	45	45	45	45	45	45	45
DW	2.47	1.69	1.86	1.24	1.25	0.46	1.97	0.56

* $p<0.1$, ** $p<0.05$, *** $p<0.01$
Note : se=standard error, s.a.=seasonal adjustment

4. Regression of Labor Productivity on Capital Intensity

(Table 15) Regression of labor productivity on capital intensity by Industry
(with time index, 2011.1 – 2022.1)

	Economy-wide		Manufacturing		Service		Primary Ind.	
	Model_1	Model_2 (s.a.)	Model_1	Model_2 (s.a.)	Model_1	Model_2 (s.a.)	Model_1	Model_2 (s.a.)
ln(K/L)	0.340***	0.469***	0.426**	0.719***	0.528***	0.602***	0.517***	0.523***
se	-0.098	-0.059	-0.182	-0.155	-0.073	-0.06	-0.09	-0.049
time	0.002**	0.001**	0.001	-0.003	0.002***	0.001***	0.001	0.001
se	-0.001	0.000	-0.002	-0.002	0.000	0.000	-0.002	-0.001
_cons	-3.575***	-2.993***	-2.248***	-2.133***	-3.758***	-3.501***	-3.695**	-3.444***
se	-0.466	-0.279	-0.09	-0.075	-0.28	-0.23	-1.591	-0.868
Adj. R^2	0.82	0.93	0.76	0.84	0.91	0.94	0.43	0.73
Obs.	45	45	45	45	45	45	45	45
DW	2.33	1.65	1.78	1.52	1.63	0.96	1.99	0.56

* p<0.1, ** p<0.05, *** p<0.01
Note : se=standard error, s.a.=seasonal adjustment

4. Regression of Labor Productivity on Capital Intensity

(Table 16) Regression of labor productivity on capital intensity by Industry
(with dummy variable, 2011.1 – 2022.1)

	Economy-wide		Manufacturing		Service		Primary Ind.	
	Model_1	Model_2 (s.a.)	Model_1	Model_2 (s.a.)	Model_1	Model_2 (s.a.)	Model_1	Model_2 (s.a.)
ln(K/L)	0.617***	0.653***	0.411***	0.423***	0.954***	1.016***	0.538***	0.541***
se	-0.073	-0.04	-0.061	-0.049	-0.082	-0.059	-0.088	-0.046
dum	-0.012	-0.017*	0.031	0.028	-0.029**	-0.037***	-0.085	-0.079**
se	-0.015	-0.008	-0.022	-0.018	-0.013	-0.009	-0.057	-0.03
_cons	-2.363***	-2.383***	-2.178***	-2.198***	-2.565***	-2.580***	-2.462***	-2.516***
se	-0.022	-0.012	-0.048	-0.039	-0.013	-0.01	-0.105	-0.054
Adj. R^2	0.79	0.93	0.77	0.84	0.88	0.94	0.45	0.76
Obs.	45	45	45	45	45	45	45	45
DW	2.57	1.93	1.96	1.39	1.52	0.59	2.04	0.63

* p<0.1, ** p<0.05, *** p<0.01
Note 1) se=standard error, s.a.=seasonal adjustment
2) dum=0 (2011.1 ~ 2019.4), 1(2020.1~2022.1)

5. Concluding Remarks

- Estimation of the work intensity index was tougher than expected because there is no consistent quarterly dataset from a single data source in Korea. However, estimation should be done anyway for the quarterly data generation. A key idea is finding a proxy variable that explains the quarterly variation. Because we don’t have detailed information about labor market, such as education level, age, or sex, KLEMS approach cannot be fully applied to our quarterly dataset. Instead, we can apply a simple growth accounting to generate the quarterly TFP.

- There are **three major findings** in the present paper. **The first finding** is that when we adjusted both capital input and labor input by Model 3, estimated profile of TFP was quite different from those of Model 1 and Model 2 and was much more volatile than those of Model 1 and Model 2. We conjecture the proxy variable (the ratio of overtime working hours / total working hours) we have chosen is very sensitive at the time of Pandemic and over business cycle,

5. Concluding Remarks

- **The second finding** is that the regression of labor productivity on capital intensity produced estimates of the coefficient of capital income share and the growth rate of TFP. The estimation with a Time Dummy Variable for Pandemic period produced negative coefficients reflecting a significant downward pressure on GDP during the pandemic-inflicted period (First Quarter 2020 – First Quarter 2022)

- The third finding is that the COVID-19 after the first quarter of 2020 has made growth rates of both GDP and labor input turn negative. But the relative contribution of capital input and TFP make up almost 90 % of GDP growth. We find the quarterly TFP estimates are exhibiting a pro-cyclical pattern which is closely related to the recovery cycle of the pandemic. We also find the quarterly TFP estimates are exhibiting a pro-cyclical pattern which is closely related to the recovery cycle of the pandemic. This finding is in contrast with the finding by Basu, Fernald and Kimball (2006) who supports technology improvements are contractionary: when technology improves, inputs and investment generally fall in the short run, and output itself may also fall.

Reference

Basu, S., J. Fernald and M. Kimball (2006), “Are Technology Improvements Contractionary?”, *American Economic Review, Volume 96 Number 5,* pp. *1418-1448*

Bureau of Labor Statistics (2007), “Technical Information about the BLS Multifactor Productivity Measures”, http://www.bls.gov/mfp/mprtech.pdf

Denison, Edward F. (1967), Why Growth Rates Differ: Postwar Experience in Nine Western Countries, The Brookings Institution

EU KLEMS (2009) EU KLEMS Growth and Productivity Accounts, Release November 2009

Fernald, John, A Quarterly Utilization-Adjusted Series on Total Factor Productivity, Federal Reserve Bank of San Francisco Working Paper 2012-19, April 2014

Reference

Basu, S., J. Fernald and M. Kimball (2006), "Are Technology Improvements Contractionary?", *American Economic Review, Volume 96 Number 5, pp. 1418-1448*

Fukao, K., T. Miyagawa, H. Pyo, K Rhee and M. Takizawa (2019), "The Impact of Information and Communications Technology Investment on Employment in Japan and Korea" in *Measuring Economic Growth and Productivity,* edited by Barbara M. Fraumeni, Chapter 13 pp. 283-297

Han, J., S. Ahn and H. Pyo (2019), A Quarterly Extension of KLEMS Database and Its Applications to Short-term Productivity Analysis in Korea (2000-2016), Paper presented at the Fifth Asian KLEMS Conference, October 14-16, 2019 Tsinghua University, Beijing

Jorgenson, D. W. and Z. Griliches (1997), "The Explanation of Productivity Change", *The Review of Economic Studies*, Vol. 34, No. 3, pp. 249-283

Pyo, H and S. Song (2014), "The Estimation of Quarterly Capital Stock and Potential GDP Growth Rates in Korea (1981-2012), *The Korean Economic Analysis*, Volume 20 Number 3, pp. 177-285, Korea Institute of Finance (in Korean)

Pyo, Hak K. (2018) Chapter 23 Productivity and Economic Development in *The Oxford Handbook of Productivity Analysis* edited by E. Grifell-Tatje, C. A. K. Lovell and R. C. Sickles, Oxford University Press

Pyo, H., H Chun and K. Rhee, *An International Comparison of Total Factor Productivity*, Korea Productivity Center, 2022 Seoul (in Korean)

Rhee, K. and Hak K. Pyo (2022), “Economic Growth and Productivity Convergence in the Korean Economy: Evidence from OECD, EU KLEMS and KIP Database” (in Korean), *Korean Economic Journal*, Volume 61 Number 1, pp. 45-109

Solow, Robert M. (1957), “Technical Change and the Aggregate Production Function”, *Review of Economics and Statistics*, 39, pp. 312-320

Timmer, Marcel P. (2000), Towards European Productivity Comparisons using the KLEMS Approach- An Overview of Sources and Methods, Groningen Growth and Development Centre and the Conference Board

Zaid Mohamed and Pat Bodger (2005), “Forecasting Electricity Consumption in New Zealand using Economic and Demographic Variables”, Energy 30, pp. 1833-1843