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A Time-Varying Connectedness Analysis of the Korean Economy *

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We examine time-varying connectedness among Korea's macroeconomic variables with a special focus on whether there are structural changes among macro variables between before- and after-Covid19 periods. From total connectedness analysis, we found that the connectedness among macro variables intensified after Covid-19. From "NET" connectedness analysis, we also found that employment shock affects other variables more than other shocks affect employment and that wage is affected by other shocks more than its shock affect other variables after Covid-19 pandemic. Net pairwise directional connectedness analysis reveals that the sign of net effect reversed between (1) total hours worked and employment, and (2) wage and employment after Covid-19. Finally, network graphs of net pairwise directed connectedness, based on the relative strength of connectedness, show that wage shock strongly affect production. CPI also affects the production while it is also affected by interest rate shock. Employment shock has significant effect on interest rate. We also provide the policy implications based on the connectedness analysis.

JEL Classification: C32, C50, E00
Keywords: TVP-VAR, connectedness, volatility spillover, Covid-19, employment

1. INTRODUCTION

Since Diebold and Yilmaz (2009, 2012, 2014), a variety of economic analysis with connectedness analysis based on forecast error variance decomposition has become popular. However, most of research interest with connectedness has mainly been focused either on the financial (stock) or on commodity markets (for example, see Ha (2022) and Ha et al. (2022) for energy market; Dong et al. (2022) and Ngene (2021) for stock market). Antonakakis et al. (2020) analyzed the connectedness for four most traded foreign exchange rates (EUR, GBP, JPY, CHF). For Korean cases, for example, Park et al. (2020) analyzed the spillover effects between economic variables and Korean financial markets (leading economic index, exchange rate, call rate, CP rate KOSPI index, etc.). Kang (2019) analyzed connectedness for index futures markets.

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However, not much research has been focused on the dynamic connectedness among macroeconomic variables, such as industrial production, employment, total hours worked, wage, interest rate and CPI. Especially, this study shows how the connectedness of macroeconomic variables during Covid-19 pandemic period is different from pre-Covid-19 period. To the best of our knowledge, this is the first study to analyze the dynamic connectedness among macroeconomic variables in Korea.

2. DATA AND METHODS

2.1. Data

We use monthly data, and the sample period is between January 2011 and July 2022, based on the data availability. The monthly data for total hour worked per person and wage per person between January 2011 and December 2019 are taken from National Statistics Office, and other variables (total hours and wages between January 2020 and July 2022; employment, CPI, industrial production, call rate between January 2011 and July 2022) are taken from Bank of Korea.[1] All the variables are seasonally adjusted and taken in into logs except interest rate. To insure stationarity, all the variables are first-differenced.

2.2. Empirical Model

We applied TVP-VAR connectedness approach as suggested by Antonakakis et al. (2020) and Gabauer (2021). The TVP-VAR(p) model is expressed as follows:

$$y_t = \Phi_t Z_{t-1} + \varepsilon_t, \quad \varepsilon_t \mid I_{t-1} \sim N\left(0, \Sigma_t\right), \tag{1}$$

$$vec\left(\Phi_t\right) = vec\left(\Phi_{t-1}\right) + \xi_t, \quad \xi_t \mid I_{t-1} \sim N\left(0, \Xi_t\right), \tag{2}$$

where I_{t-1} represents information available until $t-1$.

The connectedness approach introduced by Diebold and Yilmaz (2014) relies on generalized impulse response functions (GIRF) and generalized forecast error variance decompositions (GFEVD) which are based on the time-varying coefficient and time-varying variance-covariance

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1) Here, total hours worked per person and wage per person are for all industries and for all sizes (i.e., employment of 1 and above). Also, it is important note that those data are for “regular employees”. The original sources of total hours worked per person and wage per person is from Statistics Korea. Regular employees mean that, among paid employees, the employment is either contracted longer than 1 year or they begin to work from official hiring process so that they can get all the benefits that companies can provide. Therefore, our results presented in this paper may be different when we analyze either with temporary workers or with daily workers.

matrices retrieved from the TVP-VAR. The TVP-VAR has to be transformed to its vector moving average (VMA) representation via the World representation theorem:

$$\begin{aligned} y_t &= \Gamma'\left(\Upsilon_t(Z_{t-2}+\zeta_{t-1})+\zeta_t\right)=\Gamma'\left(\Upsilon_t\left(\Upsilon_t\left(Z_{t-3}+\zeta_{t-2}\right)+\zeta_{t-1}\right)+\zeta_t\right) \\ &\vdots \\ &=\Gamma'\left(\Upsilon_t^{k-1}Z_{t-k-1}+\sum_{j=0}^{k}\Upsilon_t^j\zeta_{t-j}\right). \end{aligned} \tag{3}$$

Taking the limit yields to

$$y_t = \lim_{k\to\infty}\Gamma'\left(\Upsilon_t^{k-1}Z_{t-k-1}+\sum_{j=0}^{k}\Upsilon_t^j\zeta_{t-j}\right)=\sum_{j=0}^{\infty}\Gamma'\Upsilon_t^j\zeta_{t-j}. \tag{4}$$

Where:

$$y_t = \sum_{j=0}^{\infty}\Gamma'\Upsilon_t^j\Gamma\varepsilon_{t-j}=\sum_{j=0}^{\infty}\Lambda_{jt}\varepsilon_{t-j},\ \Lambda_{jt}=\Gamma'\Upsilon_t^j\Gamma. \tag{5}$$

The GIRFs $\Psi_{ij,t}^g(K)$ represent the K-step-ahead responses of all variables following a shock in variable i and can be calculated by

$$GIRF_t\left(K,\iota_{i,t},I_{t-1}\right)=E\left(y_{t+K}\mid\varepsilon_{i,t}=\iota_{i,t},I_{t-1}\right)-E\left(y_{t+K}\mid I_{t-1}\right), \tag{6}$$

$$\Psi_{i,t}^g(K)=\Sigma_{ii,t}^{-\frac{1}{2}}\Lambda_{K,t}\Sigma_t\varepsilon_{i,t}\Sigma_{ii,t}^{-\frac{1}{2}}\iota_{i,t},\quad \iota_{i,t}=\Sigma_{ii,t}^{\frac{1}{2}}, \tag{7}$$

$$\Psi_{i,t}^g(K)=\Sigma_{ii,t}^{-\frac{1}{2}}\Lambda_{K,t}\Sigma_t\varepsilon_{i,t}, \tag{8}$$

where K represents the forecast horizon, $\iota_{i,t}$ the selection vector with one on the i th position and zero otherwise.

Define the GFEVD $\tilde{\psi}_{ij,t}^g(K)$ as the forecast error variance share one variable explains on others. These variance shares are then normalized, so that each row sums up to one, meaning that all variables together explain 100% of variable's i forecast error variance. This is calculated as follows

$$\tilde{\psi}_{ij,t}^g(K)=\frac{\sum_{t=1}^{K-1}\Psi_{ij,t}^{2,g}}{\sum_{j=1}^{m}\sum_{t=1}^{K-1}\Psi_{ij,t}^{2,g}}, \tag{9}$$

with $\sum_{j=1}^{m}\tilde{\psi}_{ij,t}^{g}\left(K\right)=1$ and $\sum_{i,j=1}^{m}\tilde{\psi}_{ij,t}^{g}\left(K\right)=m$.

First, the case where variable i transmits its shock to all other variables j, called total directional connectedness "TO" others, is defined as,

$$C_{i\to j}^{g}(K)=\sum_{j=1,i\neq j}^{m}\tilde{\Psi}_{ji,t}^{g}(K)\,. \tag{10}$$

Second, the shock variable i receives from variables j, called total directional connectedness "FROM" others, is computed by,

$$C_{i\leftarrow j}^{g}\left(K\right)=\sum_{j=1,i\neq j}^{m}\tilde{\psi}_{ij,t}^{g}\left(K\right)\ C_{i\to j}^{g}(K)=\sum_{j=1,i\neq j}^{m}\tilde{\Psi}_{ij,t}^{g}(K)\,, \tag{11}$$

By subtracting the total directional connectedness TO others from the total directional connectedness FROM others the "NET" total directional connectedness is obtained, which can be interpreted as the influence variable i has on the analyzed network.

$$C_{i,t}^{g}\left(K\right)=C_{i\to j,t}^{g}\left(K\right)-C_{i\leftarrow j,t}^{g}\left(K\right). \tag{12}$$

If the NET total directional connectedness of variable i is positive, it means that variable i influences the network more than being influenced by it, and vice versa.

Finally, the NET total directional connectedness is broken down even further to examine the bidirectional relationships by computing the net pairwise directional connectedness (NPDC).

$$NPDC_{ij}\left(K\right)=\tilde{\psi}_{jit}\left(K\right)-\tilde{\psi}_{ijt}\left(K\right), \tag{13}$$

where NPDC identifies whether variable i is driving variable j or being driven by it.

The total connectedness index (TCI) calculates the market interconnectedness and is constructed by

$$C_{t}^{g}\left(K\right)=\frac{\sum_{i,j=1,i\neq j}^{m}\tilde{\psi}_{ij,t}^{g}\left(K\right)}{\sum_{i,j=1}^{m}\tilde{\psi}_{ij,t}^{g}\left(K\right)}=\frac{\sum_{i,j=1,i\neq j}^{m}\tilde{\psi}_{ij,t}^{g}\left(K\right)}{m}\,. \tag{14}$$

The main problem with this measure is that the interpretation of what is a high interconnectedness is subjective. As shown in Gabauer (2021), the own variance shares are by construction always larger or equal to all cross-variance shares. This means that the TCI is within $\left[0,\frac{m-1}{m}\right]$ and not within $\left[0,1\right]$, which makes interpretations difficult. To improve interpretability, the TCI has to be slightly modified:

$$C_t^g(K) = \left(\frac{m}{m-1}\right)\frac{\sum_{i,j=1,i\neq j}^{m}\tilde{\Psi}_{ij,t}^g(K)}{m} = \frac{\sum_{i,j=1,i\neq j}^{m}\tilde{\Psi}_{ij,t}^g(K)}{m-1},\ 0 \le C_t^g \le 1\,. \tag{15}$$

The TCI can be decomposed to the pairwise connectedness index (PCI) measuring the interconnectedness between two variables i and j.

$$C_{ijt}^g(K) = 2\left(\frac{\tilde{\Psi}_{ij,t}^g(K) + \tilde{\Psi}_{ji,t}^g(K)}{\tilde{\Psi}_{ii,t}^g(K) + \tilde{\Psi}_{ij,t}^g(K) + \tilde{\Psi}_{ji,t}^g(K) + \tilde{\Psi}_{jj,t}^g(K)}\right),\ 0 \le C_{ijt}^g \le 1\,. \tag{16}$$

This metric ranges between [0,1] illustrating the degree of bilateral interconnectedness across variable i and j.

3. RESULTS

Table 1 show the summary statistics. All the variables, except interest rate, are log-differenced and multiplied by 100 such that mean of the logged differenced variables are approximately equal to growth rate in percent. Interest rate is first-differenced. Table 1 shows that wage (WAGE), industrial production (PROD) and CPI (CPI) are rising on average, and interest rates (INTR) and total hours worked (HOURS) are falling on average during the periods of February 2011 and July 2022.

Table 1 Summary Statistics

Statistic	N	Mean	St. Dev.	Min	Max
INTR	138	-0.005	0.087	-0.260	0.260
WAGE	138	0.352	5.591	-15.510	23.625
HOUR	138	-0.087	4.822	-26.563	17.144
PROD	138	0.158	1.117	-3.880	3.997
EMP	138	0.114	0.445	-2.475	1.945
CPI	138	0.151	0.332	-0.747	1.057

Note: This table lists the 19 countries in the sample and the years covered in the main regressions. The columns show the average and standard deviations of the changes in household debt to GDP and log markups for each country.

Table 2 show the dynamic connectedness table for whole period. Each row and column in table 2 denote variables and shocks, respectively. For example, "FROM" measures volatility spillovers from other shocks, excluding own shock (as in equation 10). On the other hand, "TO" measure volatility spillovers for a shock to others (as in equation 11), excluding own shock. Therefore, horizontal sum (excluding own shock) measures "FROM" and vertical sum (excluding own shock) measures "TO". "NET" measures the difference between "TO" and "FROM" (as in equation 12). Based on the "NET", we observe that wage (WAGE), hours worked (HOUR) and employment (EMP) shocks affect other variables more the other shocks affect those variables over the whole sample period.

Table 2 Dynamic Connectedness Approach Table

Statistic	INTR	WAGE	HOUR	PROD	EMP	CPI	FROM
INTR	79.41	0.87	3.08	1.70	9.69	5.24	20.59
WAGE	0.56	88.40	2.48	2.36	3.59	2.61	11.60
HOUR	1.89	2.03	91.45	1.48	1.35	1.80	8.55
PROD	2.67	9.07	1.36	78.88	4.67	3.35	21.12
EMP	5.79	3.45	1.05	4.54	83.66	1.51	16.34
CPI	9.59	2.32	2.87	1.34	2.22	81.65	18.35
TO	20.49	17.75	10.84	11.43	21.52	14.51	96.54
Inc.Own	99.91	106.15	102.30	90.31	105.18	96.15	cTCI/TCI
NET	-0.09	6.15	2.30	-9.69	5.18	-3.85	19.31/16.09
NPT	2.00	2.00	3.00	1.00	5.00	2.00	

Note: NPT denotes "Net Pairwise Transmission", cTCI denotes corrected Total Connectedness Index.

Figure 1 shows the dynamic total connectedness index (TCI) as in equation 11. TCI shows how variables of interest are strongly connected and how it changes over time. The figure shows that the total connectedness shows downward trend until the outbreak of Covid-19 pandemic. After Covid-19, the connectedness among macroeconomic variables intensified until before-2022.

Figure 1 Dynamic Total Connectedness Index (TCI)

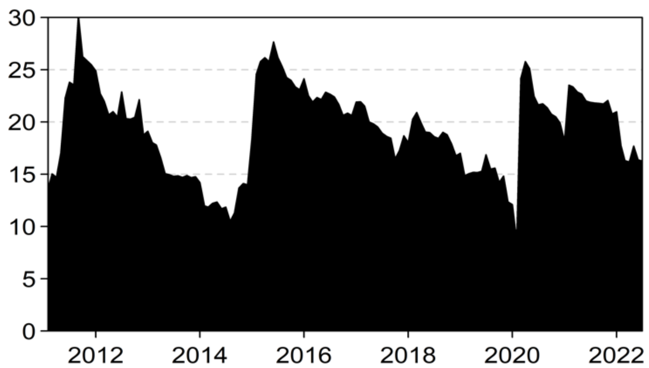


Figure 2 shows "TO" measures: the effects of each shock to other variables in aggregate. Interestingly, employment shock has much greater effects on other variables after Covid-19 pandemic than 2014-2019 period.

Figure 2 Dynamic "TO" Index

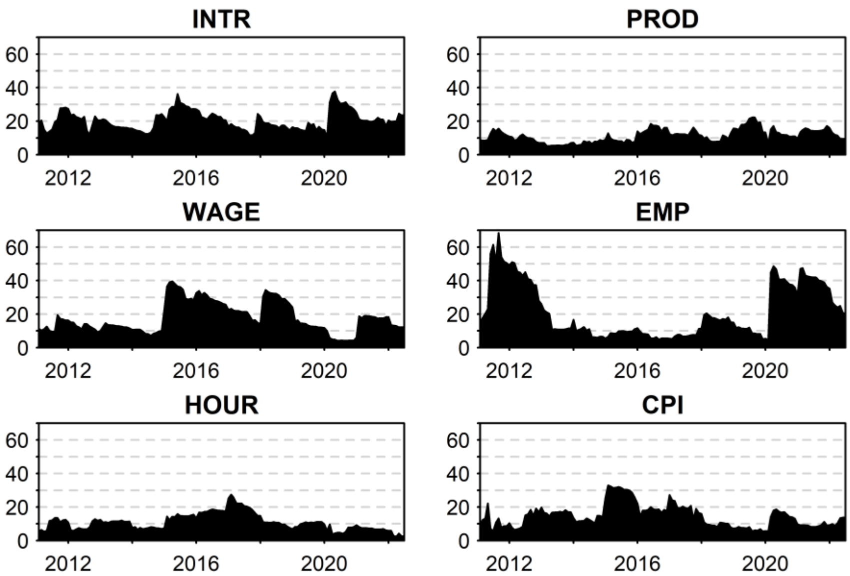


Figure 3 shows "FROM" measures: the effects of other shocks on each variable in aggregate. Again, employment also affected more by other shocks after Covid-19 periods.

Figure 3 Dynamic "FROM" Index

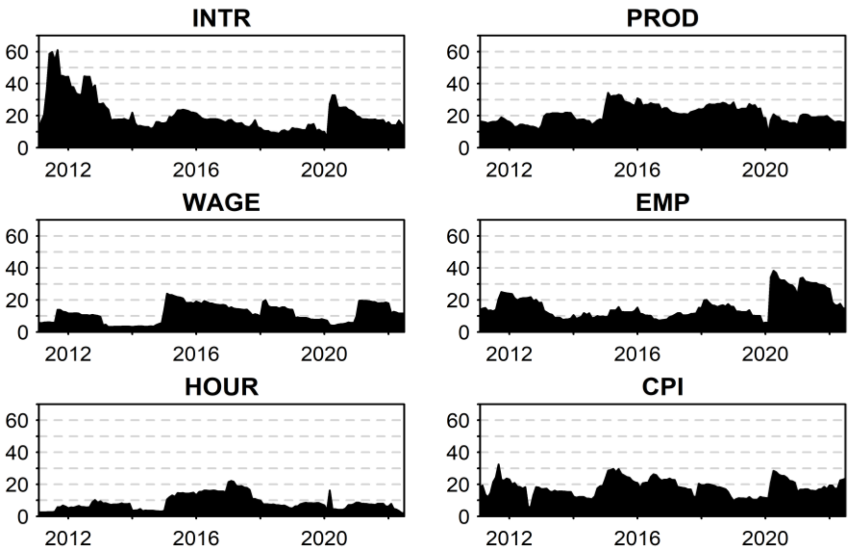


Figure 4 shows "NET" measures: the difference between "TO" and "FROM". The figure reveals three interesting findings. First, after Covid-19 pandemic, employment shock affects other variables more than other shocks affect employment. Second, after Covid-19 pandemic, wage is affected by other shocks more than its shock affect other variables after Covid-19 pandemic. Third, hours worked is affected by other shocks more than its shock affect other variables after Covid-19.

Figure 4 Dynamic "NET" Index

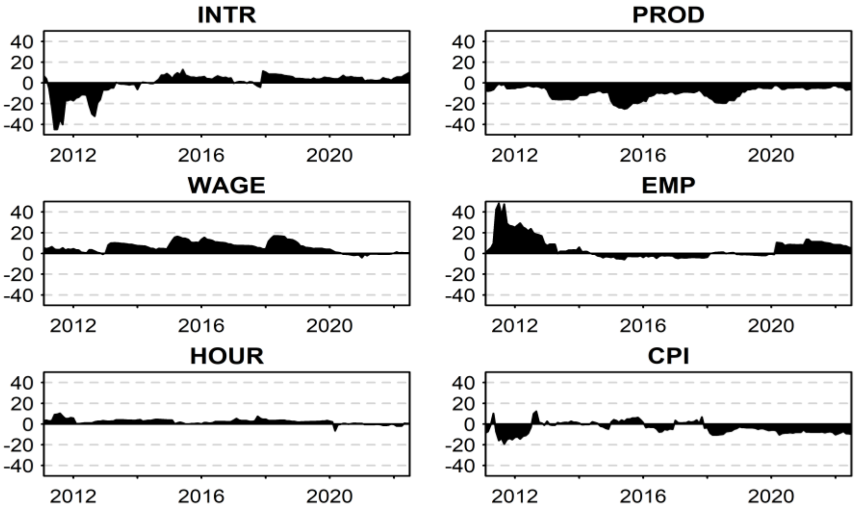


Figure 5 shows net directional pairwise connectedness. The first notable finding after Covid-19 is that the sign of net effect reversed between (1) total hours worked and employment, (2) wage and employment. Especially, before Covid-19 (at least between 2017 and 2019), shock from hours worked affects employment more than employment shock affects hours worked. However, after Covid-19, employment shock affects total hours worked more than hour shock affects employment. "Total hours worked" means (monthly) total hours per worker and it may greatly be affected by government rule, such as 52-hour workweek rule by the Korean government. Therefore, hours shock is thought to affect employment more than employment shock affect total hours (per worker). The reversal of net effect between these two variables may be due to quarantine rule from Covid-19.

Before Covid-19 period, wage shock affected employment more than employment shock affected wage. However, after Covid-19, employment shock affects wage more than wage shock affects employment. It may be due to sectoral shift of workers. During Covid-19, online-related industry is growing fast while offline industry, especially service industry, is shrinking. Also, given the limited availability of workers due to quarantine, together with the sectoral shift of workers, the barging power of wage may have increased after Covid-19 which cause a greater effect of employment shock on wage.

Figure 5 Dynamic Net Pairwise Directional Connectedness (NPDC) Index

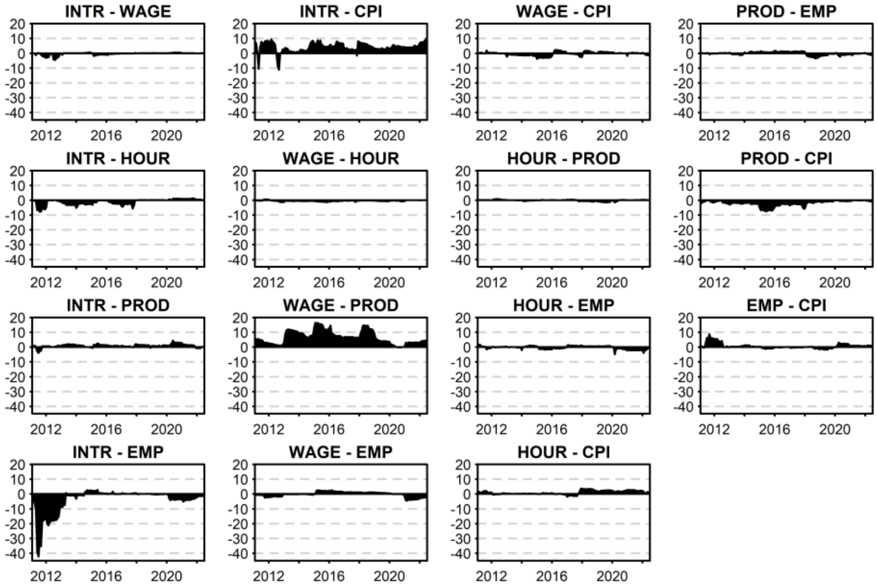
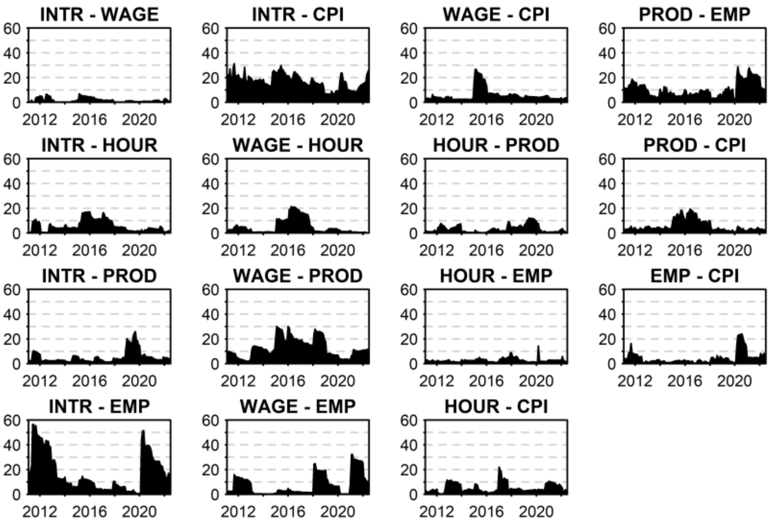


Figure 6 reports pairwise connectedness, sum of bilateral "TO" and "FROM" effects. After breakout of COVID-19 pandemic, the connectedness between (1) production and employment, (2) interest rate and employment, (3) wage and employment appears to become stronger.

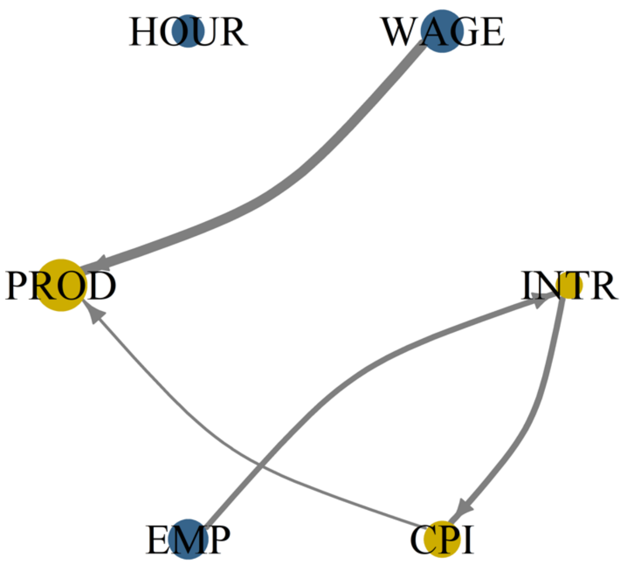
Figure 6 Pairwise Connectedness Index (PCI)



Finally, figure 7 shows network graphs of net pairwise directed connectedness based on the relative strength of connectedness. The figure shows that wage shock strongly affect production.

CPI also affects the production while it is also affected by interest rate shock. Employment shock has significant effect on interest rate.

Figure 7 Network Graph: Net Pairwise Directed Connectedness



4. CONCLUSION

Using various measures, we examine time-varying connectedness among Korea's macroeconomic variables with a special focus on whether there are structural changes among macro variables between before- and after-Covid19 periods. We first find that, from total connectedness analysis, the connectedness among macro variables intensified after Covid-19.

We also find from "NET" connectedness analysis that employment shock affects other variables more than other shocks affect employment and that wage is affected by other shocks more than its shock affect other variables after Covid-19 pandemic.

Net pairwise directional connectedness analysis reveals that the sign of net effect reversed between (1) total hours worked and employment, (2) wage and employment after Covid-19. These reversal of signs after Covid-19 may be due to quarantine rule from Covid-19 or sectoral shift of workers during Covid-19. Also, pairwise connectedness shows that, after breakout of COVID-19 pandemic, the connectedness between (1) production and employment, (2) interest rate and employment, (3) wage and employment appears to become stronger.

Finally, network graphs of net pairwise directed connectedness, based on the relative strength of connectedness, show that wage shock strongly affect production. CPI also affects the production while it is also affected by interest rate shock. Employment shock has significant effect on interest rate.

One policy implication from network graph analysis with net pairwise directed connectedness is that wage is the most important variable. Therefore, the policy makers should avoid any policy that can cause a drastic rise in the wage, such as minimum wage.

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