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**Online Appendix for**

**Macroeconomic Impact of Oil Shocks: A Large-Scale Bayesian SVAR Approach in South Korea**

**By**

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## Appendix

### A. Descriptive Statistics

Table [1] presents the statistical descriptions of the oil market and macroeconomic variables. Crude oil production shows significant periodic increases. Changes in production capacity or geopolitical tensions over the observed period affect oil extraction. Real economic activity displays high global demand for commodities, mirroring the global economic conditions, including oil. Meanwhile, real crude oil prices demonstrate considerable variation, indicative of the intricate interplay between supply dynamics, geopolitical tensions, and shifts in global demand patterns.

Regarding the macroeconomic indicators of South Korea, the inflation rate indicates that prices have, on average, been rising at a relatively slow and steady pace. This suggests that the economy has experienced a period of price stability, with minimal fluctuations in the general level of prices. The average interest rates growth is relatively low, this may be a result of the implementation of accommodative monetary policies, in a low inflation environment, to stimulate economic growth without risking excessive inflationary pressures. Exchange rate, imports, exports, and the foreign direct investment have the highest standard deviations than the other macroeconomic variables. The results imply that they are more susceptible to external shocks and uncertainties. Except the oil production and the industrial production variables, all the variables have positive skewness reflecting long right tail. This means that on average these variables tend to be greater than the mode.

	Mean	S.D.	Max	Min	Skew	Kurt	$\hat{\rho}(1)$
<b><math>\Delta OP</math></b>	0.01	0.03	0.09	-0.14	-1.30	4.13	0.88
<b>REA</b>	8.67	71.20	189.35	-161.42	0.34	-0.13	0.92
<b>RPO</b>	7.81	0.42	8.67	6.48	0.44	-0.37	0.95
<b><math>\Delta IP</math></b>	0.03	0.03	0.15	-0.09	-0.01	1.37	0.82
<b>INF</b>	0.03	0.01	0.06	-0.00	0.31	-0.51	0.96
<b>IR</b>	0.03	0.01	0.05	0.00	0.12	-1.13	0.99
<b><math>\Delta MS</math></b>	0.08	0.03	0.17	0.02	0.39	-0.32	0.96
<b><math>\Delta FX</math></b>	0.01	0.11	0.63	-0.24	2.00	7.30	0.90
<b><math>\Delta IM</math></b>	0.08	0.22	0.56	-0.28	1.14	1.63	0.95
<b><math>\Delta EX</math></b>	0.00	0.09	0.39	-0.17	2.04	8.76	0.92
<b><math>\Delta FDI</math></b>	0.33	0.86	5.37	-0.87	2.10	6.27	0.16

*Table 1 Descriptive Statistics  $\Delta OP$  (Percentage Change in Global Crude Oil Production); REA (Real Economic Activity, Kilian Index); RPO (Global Real Price of Brent Crude);  $\Delta IP$  (change in Korean industrial production index); (INF) inflation (change in consumer price index inflation growth); IR (market interest rate in percent per annum);  $\Delta MS$  (percentage change in money supply M2);  $\Delta FX$  (percentage change in the Exchange rate);  $\Delta IM$  (percentage change in total imports);  $\Delta EX$  (percentage change in total exports);  $\Delta FDI$  (percentage change in foreign direct investment abroad);*

## B. Lag Selection

The lag of the LB-SVAR models is determined through Bayesian model comparison. This process evaluates how well each model fits the data using log marginal likelihood ( $\ln ML$ ). Table [2] shows the log marginal likelihood estimates for the 7 different lags in the LB-SVAR model. The optimal lag is selected by the highest value of the ( $\ln ML$ ). Therefore, we use  $p = 3$  in our empirical analysis. The difference from the second-best model ( $p = 2$ ) in the  $\ln ML$  is about 8 which means statistically significant. We also confirm that the  $\ln ML$  gradually decreases as the penalty term for model complexity increases when the lag is greater than 3.

	1.0000	2.0000	3.0000	4.0000	5.0000	6.0000	7.0000
<b><math>\ln ML</math></b>	141.6363	208.0574	215.9467	200.5216	205.8493	207.0160	207.5814

*Table 2 Lag Selection This table shows the log marginal likelihood ( $\ln ML$ ) estimates for Large Bayesian VAR model with lag lengths from 1 to 7. The results suggest the  $p = 3$  lag best fits the data.*