

Summary

In this paper, I try to 1.) replicate and update the structural vector autoregressive (SVAR) model implemented by Miyao (2002) in the analysis of the monetary policy effect in Japan, and 2.) compare the out-of-sample forecasting performance of vector autoregressive (VAR) model and univariate autoregressive (AR) model using the data from 1978:4 up to 2017:11. SVAR and VAR model consist of call rates (r), money (m), stock prices (p_k) and output (y), all in first differences, as in Miyao (2002), but the span is different because of the availability of data. The result of the analysis is somewhat different especially regarding the persistence of the monetary effect in the long run¹. The effect of the monetary policy has a limited effect on output and stock price, and is not persistent as opposed to Miyao (2002). In addition, when the dataset is updated, the monetary policy effect is even more limited with unreasonably wide confidence interval. As for the forecasting, mean squared error is not very different between VAR and AR models for all the variables considered.

Dataset

The selection of the variables are based on Miyao (2002) which has used collateralised and uncollateralised overnight rate, logarithm of money supply(M2+CD) with seasonal adjustment, logarithm of Nikkei 225 Average Index and seasonally adjusted Index of Industrial Production (IIP) that span from January 1975 to April 1998. The use of collateralised rate is due to the lack of uncollateralised rate before July 1985. Since collateralised rate is lower than the uncollateralised rate, two series are linked by adding the average difference of the overlapping period to collateralised series.

Two changes are made for this analysis due to the technical reasons. First, I change the starting date of dataset to January 1978. This is because IIP before January 1978 is not available in Ministry of Economy, Trade and Industry (METI). Second, I use money stock instead of money supply for the period after April 2003. This stems from the change in the statistics and smoothing is done in the same method for call rate.

Call rate and money stock are sourced from Bank of Japan's website (<http://www.boj.or.jp/>). Nikkei 225 and IIP are retrieved from Yahoo Finance (<https://finance.yahoo.com/>) and METI's webpage (<http://www.meti.go.jp/>), respectively.

¹ It is possible (or highly likely, honestly) that this difference stems from my mistake in coding or processing of data. The dataset and the code is available in my GitHub page (https://github.com/yoshiki146/Applied_TimeSeries_Analysis)

Empirical Results

Prior to the implementation of the models, I take preliminary unit root/cointegration test. First, I perform augmented Dickey Fuller (1979) tests and find no rejection (Table 1). I therefore take the first difference (denoted by Δ) and unit root is eliminated for all the series except for money stock. This suggests money stock may not follow $I(1)$, but since original article suggest taking first differences and $I(1)$ makes theoretical sense, I just take first difference and treat money stock as $I(1)$ ².

Table 1: ADF test result		
variable	1978:1-1998:4	1978:1-2017:11
r	-3.16 (6) *	-3.18 (7) *
m	-0.44 (6)	-2.38 (7)
p_k	-0.53 (6)	-2.07 (7)
y	-1.31 (6)	-2.78 (7)
Δr	-4.26 (12) ***	-5.99 (12) ***
Δm	-2.64 (12)	-2.76 (12)
Δp_k	-4.54 (12) ***	-5.74 (12) ***
Δy	-3.56 (12) **	-7.19 (12) ***
Note: Lag length in parentheses. *** $p < 0.01$, ** $p < 0.05$ and * $p < 0.1$		

I further perform Johansen's (1998) cointegration test using eigenvalue method. Table 2 shows the test statistics for no cointegration against one cointegration, which indicates the possibility of one cointegration but not clear especially for longer lags. In order to avoid spurious regression and follow the method of Miyao (2002), I assume the series to be not cointegrated and use the first differences henceforth.

Table 2: Johansen test result		
Lag	1978:1-1998:4	1978:1-2017:11
6	30.22 **	29.18 **
10	27.01 *	24.71 *

² I argue that this is due to the selection of long lag length. I used *adf.test* function of *tseries* package in R, which automatically select lag length to be truncation of the number of observations to the power of one third. In fact, when I set small lag length, the null hypothesis is rejected.

Table 2: Johansen test result		
Lag	1978:1-1998:4	1978:1-2017:11
12	22.95	21.15
Note: Lag length in parentheses. *** $p < 0.01$, ** $p < 0.05$ and * $p < 0.1$		

Now I implement SVAR model $B_0 \Delta y_t = c + B_1 \Delta y_{t-1} + B_2 \Delta y_{t-2} + \dots + B_p \Delta y_{t-12} + u_t$, where

$\Delta y_t = (\Delta r_t, \Delta m_t, \Delta p_{kt}, \Delta y)$ and $u_t \sim W.N(D)$. B_0 is a 4×4 coefficient matrix with ones on the diagonal, c is a vector of length four, B_1, \dots, B_p are 4×4 coefficient matrix and u_t is a structural disturbance term that follows diagonal 4×4 matrix. For unique identification, I use recursive constraint which assumes B_0 to be lower triangular. Miyao (2002) discusses the order of variables in Section one and concludes that Bank of Japan sets call rate prior to money supply (money stock)³. I choose 12 lag length since this a monthly observation and is consistent with the original research.

Figure 1 shows the impulse response up to 40 month for the period of 1978:4 - 1998:4. 95% confidence bands are computed by a Monte Carlo simulation of 1,000 replications. The effect of a call rate disturbance, shown in the first column, indicates that contractionary monetary policy decreases the money stock, stock price and output in the short run. However, the effect converges to zero in the long run which is not consistent with the original research (Figure 2).

Second column shows the impulse response to a monetary base disturbance. A rise in the call rate indicates that money demand disturbance is the driver for the shock in monetary base. The rise in stock price and output in the short term implies the positive effect of monetary easing and consistent with Miyao. No long-run effect indicates the neutrality of money, but is not consistent with the original work.

Stock price disturbance is followed by an increase in the output with small confidence band. The result is also consistent with Figure 2 in the short term but not in the long term. The similar result is found in Figure 3, which uses the updated data. Fourth column implies that output shock may increase the interest rate but not indicative for other series.

Figure 3 is an update of Figure 1 using data up to 2017:11. The result is similar to some extent for stock price disturbance and output disturbance, but have poor performance overall.

³ This may not be plausible in light of the recent massive quantitative easing by governor Kuroda.

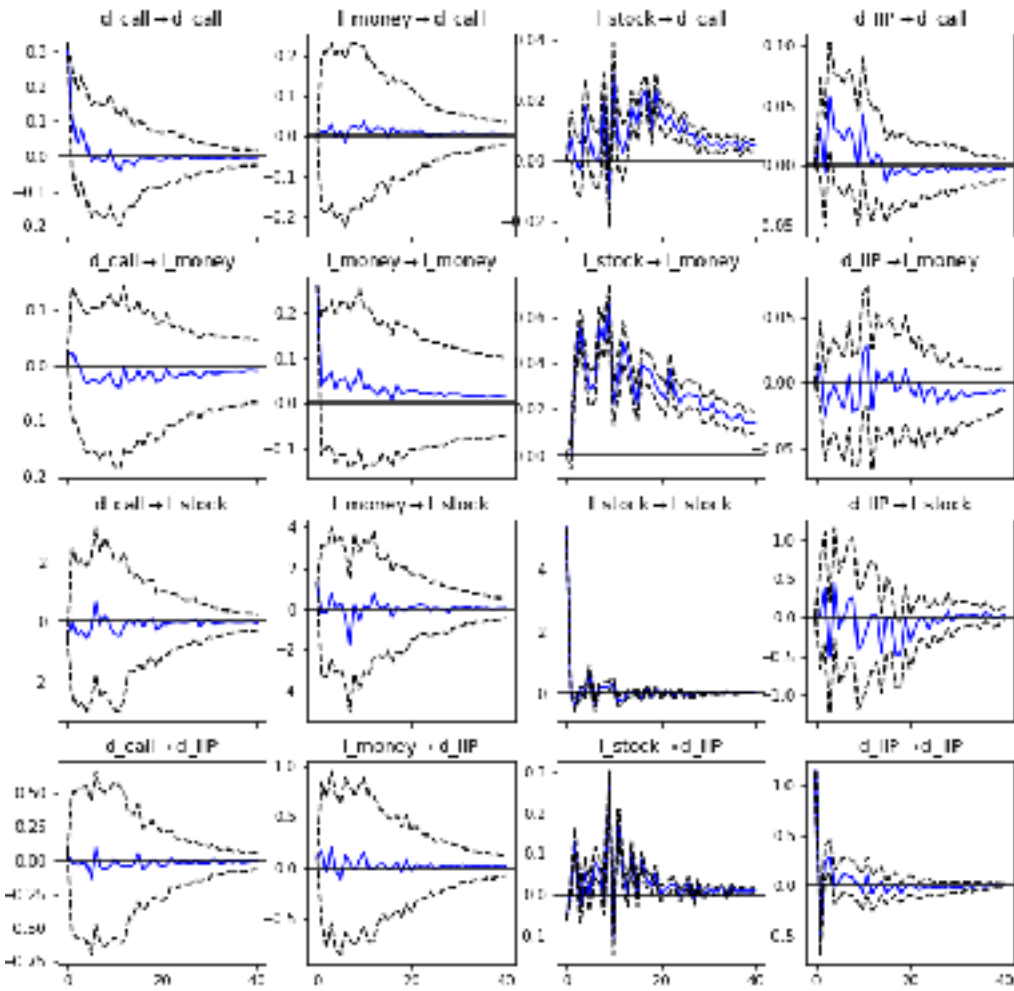


Figure 1: Impulse response for 1978:4-1998:4

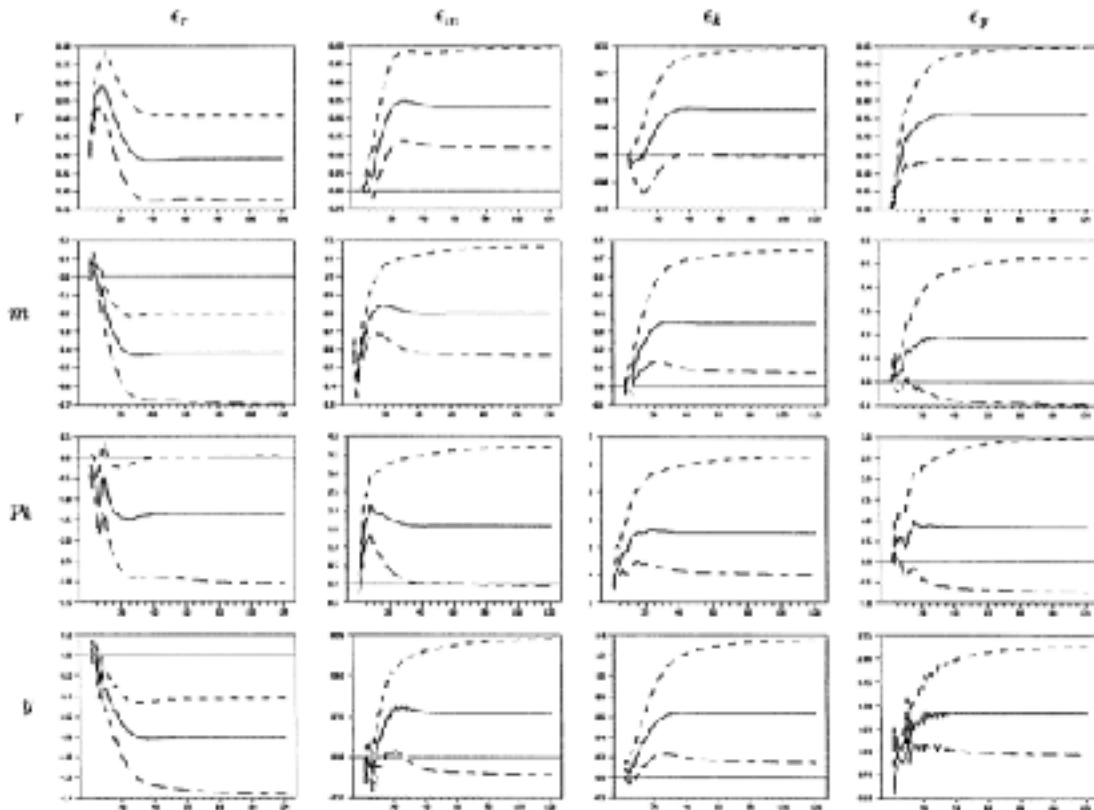


Figure 2: Impulse response in Miyao (2002)

As second part of the analysis, I compare the performance of the one month ahead forecasts between

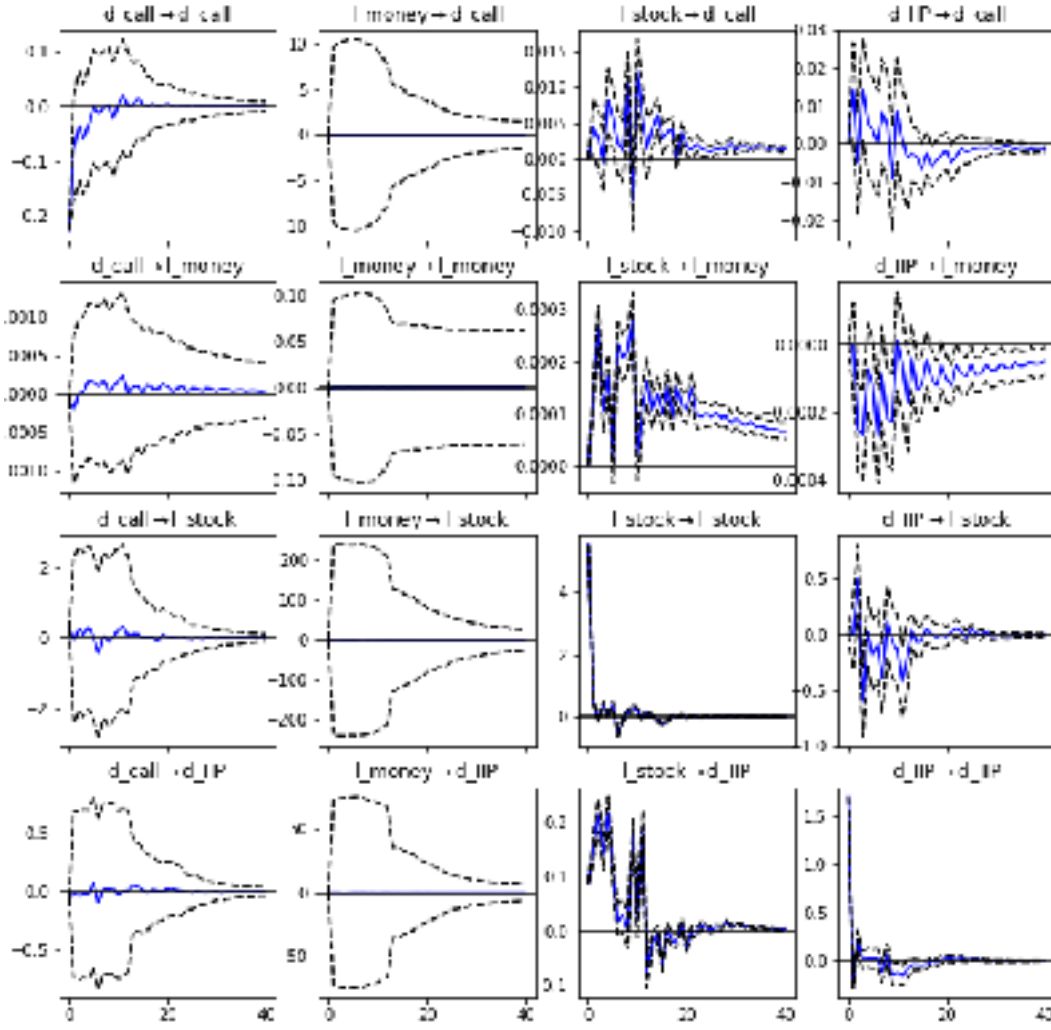


Figure 3: Impulse response for 1978:4-2017:11

VAR model and univariate AR models based on MSE for one month horizon

$(\Delta y_{t+1|t} = c + \phi_1 \Delta y_t + \dots + \phi_p \Delta y_{t-p} + \epsilon_{t+1})$. Δy_t is a vector of four variables or one of the four variables in VAR and AR, respectively. Lag length are selected based on AIC for every forecast. Forecasted period spans 1998:5-2017:11.

The MSEs, shown in Table 3, are quite similar for each series, indicating that including additional variables do not improve the performance of forecast. Stock and Watson (2002) also find the little difference between two method. They argue that forecast performance increases when factors are used for VAR model which are constructed from much more variables using principal component analysis.

Table 3: Out of Sample Forecasting Result, one month horizon		
Variable	MSE (VAR)	MSE (Univariate AR)
Δr	4.56×10^{-4}	8.6×10^{-5}
Δm	5.08×10^{-6}	4.43×10^{-6}
Δp_k	32.64	32.56
Δy	5.01	4.80

References

- Miyao, R., 2002. The effects of monetary policy in Japan. *Journal of Money, Credit, and Banking*, 34(2), pp.376-392.
- Stock, J.H. and Watson, M.W., 2002. Macroeconomic forecasting using diffusion indexes. *Journal of Business & Economic Statistics*, 20(2), pp.147-162.