Monetary Policy and Private Investment in India: The MIDAS Experience

Debasis Rooj and Reshmi Sengupta

Abstract Recent evidence shows that Indian economy is experiencing a slowdown in private investment. Even after a significant decline in interest rates over the last two years, credit growth, particularly industrial credit growth, and private investment have remained sluggish. We examine the link between monetary policy and private investment in India by applying mixed-frequency vector autoregressive (MIDAS-VAR) method to monthly yield on 91-day T-bill, a proxy for monetary policy tool on quarterly bank loans, private investment, and gross domestic product. Mixed-frequency regression analysis includes variables of different frequencies into the analysis without the need for aggregating the higher-frequency variables into lower-frequency ones. Converting higher-frequency variables into lower-frequency variables often referred to as temporal aggregation is known to have an adverse impact on statistical inferences. MIDAS performs better in recovering the causal relationships between variables released at different frequencies when compared to the conventional common low-frequency approach by allowing having heterogeneous impacts on a low-frequency variable within each low-frequency time period. The mixed-frequency analysis reveals an interesting mix of results linking the monetary policy to the private investment in India. A comparative analysis with single-frequency (quarterly) analysis underestimates the influence of monetary policy. The mixed-frequency approach, therefore, yields richer economic insights into India's sluggish investment than the classical single-frequency approach.

Keywords Monetary policy · Mixed-frequency data analysis · Private investment · Indian economy

D. Rooj (✉) · R. Sengupta
FLAME University, Pune, India
e-mail: debasis.rooj@flame.edu.in

N. R. Bhanumurthy et al. (eds.), *Advances in Finance & Applied Economics*,
https://doi.org/10.1007/978-981-13-1696-8_8

1 Introduction

Private investment is considered to be an essential driver of economic growth. It is a reflection of expectations about the future economic activity. Private investment generally contributes significantly toward the business cycle. Schembri (2017) argues that private investment contributes to the productive capacity which is essential for the sustainable increases in living standards of a nation. Hence, it is crucial that countries focus on continuously improving their private investment scenario to promote higher economic growth.

India is one of the fastest economies in the world. However, if we carefully look at the Indian growth story, one strange aspect that comes out is that India's sluggish private investment. Even though India is growing at close to 7%, private investment growth has remained muted in India. The share of private investment with respect to GDP has mostly remained at the level of 30% of the GDP and has not shown significant improvement. In fact, after reaching a high of 38% in the first quarter of 2013, it has shown only downward movement. Therefore, it is crucial to examine the causes behind such sluggishness in the private investment. Over the last two years, the Reserve Bank of India (RBI) has significantly decreased the benchmark interest rate. However, that has not helped the private investment scenario in India. The primary question remains what caused such investment slum. The problem could be due to firm-specific factors or bank-specific factors, or it could be related to some other macroeconomic factors affecting both firms and banks. Firms may be discouraged to invest whether their current or expected future profit decreases. On the other hand, banks facing credit crunch may take a stricter lending attitude which might further prohibit private investment. Overall economic environment and aggregate demand may also influence investment decisions.

This paper re-examines the factors driving the private fixed investment in India over the last decade. Understanding the underlining causes of the investment slowdown is essential for formulating policy responses that would promote private investment in India.

A large body of the literature has attributed the post-2008 economic crisis sluggishness in private investment in advanced economies to uncertainty (e.g., Barkbu et al. 2015; Lewis et al. 2014; Bussière et al. 2015). International Monetary Fund (IMF 2015) fond that subdued aggregate demand was responsible for the weakness in investment. Leboeuf and Fay (2016) examined some of the advanced economies and found that the primary driver behind the post-crisis weakness in investment is pessimism on the part of firms about foreign demand prospects. Heightened uncertainty, tight credit conditions, and weak corporate profits also attribute toward the slowdown in investment.

Empirically, Saarenheimo (1995) using vector autoregression (VAR) shown that credit supply played a statistically significant and economically important role in determining investment in Finland. On the other hand, Sadahiro (2005) using VAR found that the investment slump post-1990 in Japan was Granger-caused by a decrease in firm profit and not by bank credit. Hence, empirical evidence suggests toward mixed evidence of factors contributing toward private investment sluggishness. In the Indian context, Anand and Tulin (2014) argued that compared to standard macro-financial variables, economic policy uncertainty better explained the recent investment slowdown. In a recent paper, Das and Tulin (2017) used firm-level data and found that the debt burdens of Indian firms are the primary reason behind India's sluggish private investment. They observed that firms with higher financial leverage and firms with lower earnings relative to their interest expenses prefer to invest less.

The key variables used in the previous studies include private investment, banking lending for investment, and firm profit. These variables are generally sampled at a quarterly frequency. On the hand, other variables, such as stock prices and interest rates, are available at monthly and even higher frequencies. Most of the previous studies used some form of temporal aggregation method to convert high-frequency variables into low-frequency variables. For instance, Motonishi and Yoshikawa (1999) and Sadahiro (2005) used quarterly data of Japan for their analysis. However, temporal aggregation may cause an adverse impact on statistical inference (Silvestrini and Veredas 2008).

In this paper, we use the newly developed mixed-frequency data analysis approach of Ghysels et al. (2004), Ghysels et al. (2016), and Andreou et al. (2010). The analysis of mixed frequency is often referred as the mixed data sampling (MIDAS) regression. MIDAS regression leads to more efficient estimation compared to the classical approach of aggregating all the time series into a single frequency (Ghysels et al. 2004).

The multivariate mixed-frequency models have since been independently introduced by McCracken et al. (2015), Anderson et al. (2016), and Ghysels (2016). In this paper, we follow Ghysels' (2016) mixed-frequency VAR (henceforth MF-VAR). This methodology is straightforward and easy to implement and does not rely on any filtering procedure.

The remainder of the paper is structured as follows. In Sect. 2, we describe the MF-VAR methodology. In Sect. 3, we explain our data and provide some descriptive analysis. In Sect. 4, we present our empirical results. Section 5 concludes the paper.

2 Methodology

In this section, we first present the single-frequency VAR model and then mixed-frequency VAR model (Motegi and Sadahiro 2018) to show that the choice of sampling frequency can change empirical results considerably.

2.1 Quarterly VAR Model

Let t ∈ {1, …, n} indicate each quarter. Let SR_t^Q be the short-term interest rate. Superscript 'Q' is used to distinguish a quarterly level from a monthly level. Let C_t be the growth rate of the outstanding stock of bank credits; let π_t be the growth rate of firm profit. Finally, let I_t be the growth rate of private investment. For each series, the growth rate implies 100 times log difference of original series from the previous year. The year-to-year difference is taken to remove stochastic trends and seasonality.

As a benchmark, we formulate a quarterly VAR (4) model:

$$\begin{bmatrix} SR_t^Q \\ C_t \\ \pi_t \\ I_t \end{bmatrix} = \sum_{k=1}^{4} \begin{bmatrix} a11,k & a12,k & a13,k & a14,k \\ a21,k & a22,k & a23,k & a24,k \\ a31,k & a32,k & a33,k & a34,k \\ a41,k & a42,k & a43,k & a44,k \end{bmatrix} \begin{bmatrix} SR_{t-k}^Q \\ C_{t-k} \\ \pi_{t-k} \\ I_{t-k} \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \\ \epsilon_{4t} \end{bmatrix} \quad (1)$$

Lag length is set to be 4 so that we can capture potential seasonality left after the year-to-year differencing. A constant term is omitted to save the number of parameters. We demean each series before fitting the model.

2.2 Mixed-Frequency VAR

We now present the MF-VAR of Ghysels (2016). Our model consists of monthly interest rate and quarterly C, π and I. Hence, the quarterly interest rate is presented as

$$SR_t^Q = \frac{1}{3}\sum_{j=1}^{3} SR_{jt} \quad (2)$$

Thus, $\{SR_{1t}, SR_{2t}, SR_{3t}\}$ represent the monthly interest rates, and SR_t^Q represents the quarterly interest rate.

The MF-VAR model is as follows:

$$\begin{bmatrix} SR_{1t} \\ SR_{2t} \\ SR_{3t} \\ C_t \\ \pi_t \\ I_t \end{bmatrix} = \sum_{k=1}^{4} \begin{bmatrix} a11,k & a12,k & a13,k & a14,k & a15,k & a16,k \\ a21,k & a22,k & a23,k & a24,k & a25,k & a26,k \\ a31,k & a32,k & a33,k & a34,k & a35,k & a36,k \\ a41,k & a42,k & a43,k & a44,k & a45,k & a46,k \\ a51,k & a52,k & a53,k & a54,k & a55,k & a56,k \\ a61,k & a62,k & a63,k & a64,k & a65,k & a66,k \end{bmatrix} \begin{bmatrix} SR_{1t-k} \\ SR_{2t-k} \\ SR_{3t-k} \\ C_{t-k} \\ \pi_{t-k} \\ I_{t-k} \end{bmatrix} + \begin{bmatrix} \epsilon_{1t} \\ \epsilon_{2t} \\ \epsilon_{3t} \\ \epsilon_{4t} \\ \epsilon_{5t} \\ \epsilon_{6t} \end{bmatrix} \quad (3)$$

or in a compact form, the above equation can be written as follows

$$Y_t = \sum_{k=1}^{4} A_k Y_{t-k} + \epsilon_t \tag{4}$$

Lag length is set to be 4 for a fair comparison with the quarterly model.

A key feature of (3) is that SR_{1t}, SR_{2t}, and SR_{3t} are stacked in a vector. To see an advantage of this approach, pick the last row of (3).

$$I_t = \sum_{k=1}^{4} \left[\sum_{j=1}^{3} a_{6j,k} SR_{j,t-k} + a_{64,k} C_{t-k} + a_{65,k} \pi_{t-k} + a_{66,k} I_{t-k} \right] + \epsilon_{6,t}$$

Since $a_{61,k}, a_{62,}$ and $a_{63,k}$ can take different values from each other, $SR_{1,t-k}$, $SR_{2,t-k}$ and $SR_{3,t-k}$, are allowed to have heterogeneous impacts on I_t

Recall from (1) and (2) that the quarterly VAR(4) model implies that

$$I_t = \sum_{k=1}^{4} \left[a_{41,k} \left(\frac{1}{3} \sum_{j=1}^{3} SR_{j,t-k} \right) + a_{42,k} C_{t-k} + a_{43,k} \pi_{t-k} + a_{44,k} I_{t-k} \right] + \epsilon_{4,t} \tag{5}$$

Equation (5) assumes implicitly that $SR_{1,t-k}$, $SR_{2,t-k}$ and $SR_{3,t-k}$ have a homogeneous impact of $a_{41,k}/3$ on I_t. This classification rules out the possibility of seasonal effects and lagged information transmission within each quarter. Hence, the MF-VAR is more flexible than the quarterly VAR. In terms of asymptotic theory, MF-VAR can be treated in the same way as classical VAR—note that MF-VAR model (4) has an identical appearance with a standard VAR with six variables. Standard regularity conditions, therefore, all carry over to MF-VAR. First, we assume that all roots of the polynomial $det\left(I_6 - \sum_{k=1}^{4} A_k Z^k\right) = 0$ lie outside the unit circle, where det(·) means the determinant. Second, $\{\epsilon_t\}$ is a strictly stationary martingale difference sequence with a finite second moment. Third, $\{X_t, \epsilon_t\}$ obeys α-mixing. These assumptions ensure the consistency and asymptotic normality of least squares estimator $\widehat{A_k}$.

We perform impulse response analysis and forecast error variance decomposition for both the quarterly model and mixed-frequency model. We follow the standard Cholesky order. We set SR → C → π → I for the quarterly model and SR1 → SR2 → S R3 → C → π → I for the mixed-frequency model. These orders are in line with actual data announcement schedules in India.

3 Data

In India, the Reserve Bank of India (RBI) conducts the monetary policy. RBI uses repo rate as the primary policy instrument. Before 1997, the monetary policy used to be reviewed twice in a financial year. Then, the review process moved to quarterly frequency. At present, RBI follows a bimonthly system of announcing its policy statement from April 2014. For our analysis, we consider the yield on the 91-day Treasury bill (T-bill) from the RBI database as a monetary policy tool, where the yield is reported in monthly frequency. This will help in capturing the heterogeneous impact of the monetary policy on investment in India, which is our primary goal.

The second variable is the bank loan (C), and we use the market value of the credit for all the sectors for the private non-financial firms in India. This series is available from the Bank of International Settlements (BIS) Web site under the category credit to the non-financial sector.

Private investment (I), the primary variables of concern in our analysis, is the gross fixed capital formation (GFCF). This variable is available in quarterly frequency. The variable is obtained from OECD database (the base year is 2010). For firm profit data (π), we rely on the data on profit of the private corporate sector from Oxford Economics. This variable is available in quarterly frequency. Our analysis covers the period from 2005 Q1 to 2016 Q4 having 47 quarterly observations.

3.1 Descriptive Data Analysis

Figure 1 plots the monthly interest rates corresponding to each quarter, year-to-year growth rates of quarterly bank loans, firm profit, and private investment from 2005 Q2 to 2016 Q4. From Fig. 1, it is observed that apart from some intervals; there is no apparent correlation between interest rate and bank lending. A similar pattern is observed for firm profit and private investment. However, firm profit and investment seem somewhat correlated. Interestingly, post-2013, even after a significant decline in the interest rate, the growth of the bank lending, firm profit, and private investment has remained stagnant questioning the role of monetary policy in spurring India's investment growth.

Table 1 reports sample statistics of SR1, SR2, SR3, SRQ, C, π, and I. We find that SR1, SR2, and SR3 have some exciting differences. First, the mean is 6.944, 7.115, and 7.073%. The minimum of SR3 is higher than that of SR1 and SR2. On the other hand, maximum of SR2 is higher than that of SR1 and SR3. Second, their skewness is −0.414, −0.277, and −0.778, respectively. SR2 thus has weaker asymmetry than

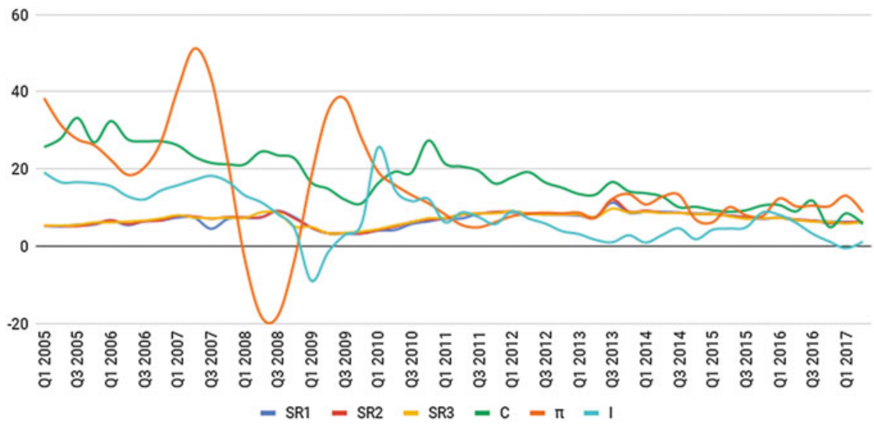

Fig. 1 Monthly interest rates, quarterly bank loans, firm profit, and private investment. *Source* Authors' own calculation. *Note* SR1, SR2 and SR3 represent the short-term interest rate (yield from 91-day T-bill) stacked monthly, while SRQ represents the average quarterly interest rate. C is growth in bank credit, π is growth in corporate profit, and I represents growth in private fixed investment. C, π, and I are quarterly percentage change (annualized)

Table 1 Descriptive statistics

	SR1	SR2	SR3	SRQ	C	π	I
Mean	6.944	7.115	7.073	7.044	7.211	5.649	3.684
Median	7.269	7.352	7.269	7.311	7.080	4.564	3.096
Min	3.235	3.275	3.316	3.316	1.814	−8.745	−4.516
Max	11.257	12.022	9.695	10.991	12.782	17.948	10.796
Std. Dev	1.727	1.715	1.534	1.626	2.757	5.179	3.015
Skewness	−0.414	−0.277	−0.778	−0.504	0.160	−0.230	−0.150
Kurtosis	3.053	3.725	2.970	3.236	2.045	4.387	3.097

Source Authors' own calculation
Note SR1, SR2 and SR3 represent the short-term interest rate (yield from 91-day T-bill) stacked monthly, while SRQ represents the average quarterly interest rate. C is growth in bank credit, π is growth in corporate profit, and I represents growth in private fixed investment. C, π, and I are quarterly percentage change (annualized)

SR1 and SR3. The heterogeneous characteristics of SR1, SR2, and SR suggest a potential benefit of the MF-VAR.

Table 2 reports contemporaneous and lagged correlation coefficients between each pair of variables, where lags are taken up to $k = 4$. Results from Table 2 are consistent with the lead/lag relationships observed in Fig. 1. We find that the contemporaneous correlation between bank credit and interest rate (SRQ_t) is positive and small. Similar correlations are observed for $SR1_t$, $SR2_t$, and $SR3_t$. Moreover, we also find that the

Table 2 Contemporaneous and lagged correlation coefficients

	$SR1_t$	$SR2_t$	$SR3_t$	SRQ_t	C_t	π_t	I_t
$SR1_t$	1.000						
$SR2_t$	0.962	1.000					
$SR3_t$	0.908	0.945	1.000				
SRQ_t	0.979	0.990	0.969	1.000			
C_t	0.030	0.121	0.137	0.096	1.000		
π_t	−0.495	−0.403	−0.414	−0.448	−0.058	1.000	
I_t	−0.052	0.080	0.163	0.061	0.473	0.080	1.000

Source Authors' own calculation
Note SR1, SR2 and SR3 represent the short-term interest rate (yield from 91-day T-bill) stacked monthly, while SRQ represents the average quarterly interest rate. C is growth in bank credit, π is growth in corporate profit, and I represents growth in private fixed investment. C, π, and I are quarterly percentage change (annualized)

contemporaneous correlation between short-term interest rate and investment is also insignificant. Interestingly, we find that the contemporaneous correlation between $SR1_t$ and I_t is −0.052, but for $SR3_t$ and I_t, it is 0.163. Next, the correlations between I_t and SRQ_{t-k} are −0.195, −0.450, −0.488, and −0.546 for $k = 1, \ldots, 4$. There is a large impact of SRQ on I with four-quarter lags. If we replace SRQ_{t-k} with $SR1_{t-k}$, $SR2_{t-k}$, or $SR3_{t-k}$, we find similar evidence. We also find that the correlations between I_t and π_{t-k} are 0.331, 0.575, 0.657, and 0.524 for $k = 1, 2, 3, 4$. There is a large impact of π on I with three quarter lags. As seen from Table 2, each variable (especially C) has high autocorrelations. An autocorrelation coefficient at lag 1 is 0.822 for SPQ, 0.889 for C, 0.802 for π, and 0.546 for I.

	$SR1_{t-1}$	$SR2_{t-1}$	$SR3_{t-1}$	SRQ_{t-1}	C_{t-1}	π_{t-1}	I_{t-1}
$SR1_t$	0.770	0.788	0.873	0.825	−0.003	−0.481	0.103
$SR2_t$	0.744	0.774	0.861	0.807	0.065	−0.355	0.198
$SR3_t$	0.714	0.753	0.841	0.783	0.078	−0.283	0.247
SRQ_t	0.759	0.788	0.877	0.822	0.046	−0.384	0.184
C_t	−0.108	−0.030	0.040	−0.037	0.889	−0.041	0.576
π_t	−0.370	−0.359	−0.412	−0.387	0.046	0.802	−0.116
I_t	−0.282	−0.208	−0.071	−0.195	0.300	0.331	0.546

	$SR1_{t-2}$	$SR2_{t-2}$	$SR3_{t-2}$	SRQ_{t-2}	C_{t-2}	π_{t-2}	I_{t-2}
$SR1_t$	0.616	0.661	0.746	0.685	−0.070	−0.265	0.236
$SR2_t$	0.578	0.633	0.728	0.656	0.005	−0.148	0.320
$SR3_t$	0.547	0.608	0.683	0.622	0.017	−0.031	0.310
SRQ_t	0.594	0.648	0.736	0.669	−0.018	−0.156	0.293
Ct	−0.304	−0.218	−0.127	−0.225	0.796	0.122	0.618
π_t	−0.197	−0.279	−0.322	−0.269	0.187	0.331	−0.196
I_t	−0.509	−0.462	−0.338	−0.450	0.321	0.575	0.359

	$SR1_{t-3}$	$SR2_{t-3}$	$SR3_{t-3}$	SRQ_{t-3}	C_{t-3}	π_{t-3}	I_{t-3}
$SR1_t$	0.451	0.517	0.576	0.523	−0.126	0.019	0.220
$SR2_t$	0.378	0.438	0.516	0.450	−0.068	0.107	0.276
$SR3_t$	0.303	0.400	0.485	0.400	−0.051	0.218	0.322
SRQ_t	0.388	0.464	0.538	0.470	−0.085	0.113	0.276
C_t	−0.480	−0.390	−0.328	−0.411	0.681	0.355	0.704
π_t	−0.039	−0.180	−0.211	−0.143	0.302	−0.166	−0.193
I_t	−0.510	−0.451	−0.470	−0.488	0.292	0.657	0.205

	$SR1_{t-4}$	$SR2_{t-4}$	$SR3_{t-4}$	SRQ_{t-4}	C_{t-4}	π_{t-4}	I_{t-4}
$SR1_t$	0.273	0.367	0.415	0.356	−0.173	0.241	0.181
$SR2_t$	0.192	0.281	0.336	0.272	−0.102	0.303	0.184
$SR3_t$	0.156	0.236	0.280	0.226	−0.097	0.367	0.211
SRQ_t	0.213	0.303	0.353	0.293	−0.128	0.307	0.195
C_t	−0.639	−0.557	−0.489	−0.577	0.577	0.581	0.563
π_t	−0.016	−0.155	−0.152	−0.107	0.337	−0.452	−0.140
I_t	−0.546	−0.539	−0.517	−0.546	0.284	0.524	−0.052

Source Authors' own calculation

Note SR1, SR2, and SR3 represent the short-term interest rate (yield from 91-day T-bill) stacked monthly, while SRQ represents the average quarterly interest rate. C is growth in bank credit, π is growth in corporate profit, and I represents growth in private fixed investment. C, π, and I are quarterly percentage change (annualized)

4 Empirical Results

This section reports our empirical findings for the quarterly and mixed-frequency VAR models.

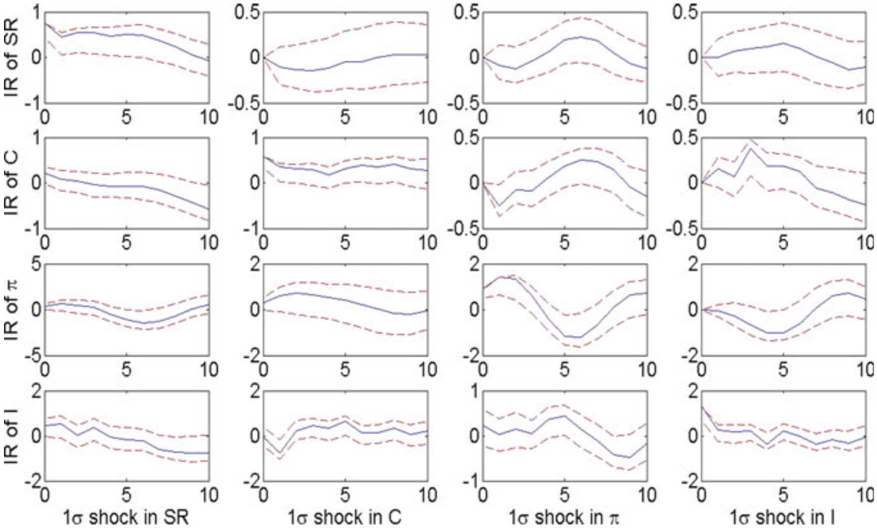

Fig. 2 Impulse response functions based on quarterly VAR(4). *Source* Authors' own calculation. *Note* SR1, SR2 and SR3 represent the short-term interest rate (yield from 91-day T-bill) stacked monthly, while SRQ represents the average quarterly interest rate. C is growth in bank credit, π is growth in corporate profit, and I represents growth in private fixed investment. C, π, and I are quarterly percentage change (annualized)

4.1 Quarterly VAR

We first present the results from the quarterly VAR model. Figure 2 plots the impulse response functions (IRFs) with 95% confidence intervals. The confidence intervals are constructed by parametric bootstrap for each horizon h = 0, 1, …, 10, using the least squares estimator $\widehat{A_k}$, error covariance estimator $\widehat{\Omega} = \left(\frac{1}{n}\right) \sum_{t=1}^{n} \hat{\epsilon}_t \hat{\epsilon}_t^{\prime}$, and normal random numbers. The number of bootstrap samples is 10,000.

It is clear from the impulse responses that the effect of the short-term interest rate on investment is insignificant. Interestingly, on the quarterly VAR model, the interest rate has no significant effect on either corporate profit or bank lending. This finding leads to question the importance of monetary policy in the real economy for India. We also find that bank credit has a negative effect on investment, but it becomes significant only at lag 1.

4.2 Mixed-Frequency VAR

We now focus on the MF-VAR(4) model. Figure 3 plots the impulse response from the mixed-frequency regression analysis. Here again, we find that firm profit has a positive but insignificant impact on the investment for India. Hence, we find no

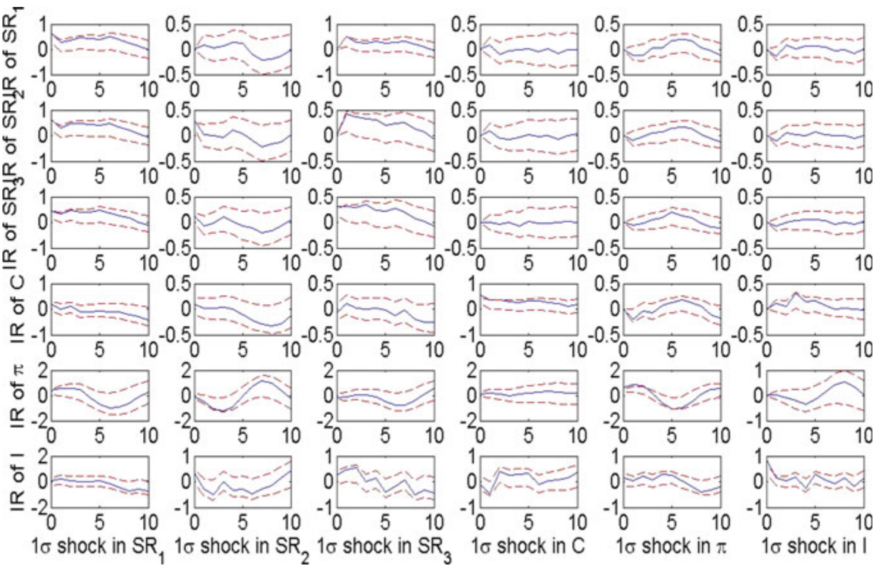

Fig. 3 Impulse response functions based on mixed-frequency VAR(4). *Source* Authors' own calculation. *Note* SR1, SR2 and SR3 represent the short-term interest rate (yield from 91-day T-bill) stacked monthly, while SRQ represents the average quarterly interest rate. C is growth in bank credit, π is growth in corporate profit, and I represents growth in private fixed investment. C, π, and I are quarterly percentage change (annualized)

evidence of the relevance of the firm-specific factor in driving the private investment in India. Also, we find that although SR1, SR2, and SR3 impact private investment differently, overall the effect remains insignificant. Moreover, the impact of bank credit impacting private investment is also insignificant suggesting strong evidence against the bank-specific factor. These results are consistent with the quarterly model.

To summarize the impulse response analysis, the MF-VAR provides an interesting picture on how investment and other variables interacted to each other. However, our analysis fails to find any evidence of either firm-specific factor, bank-specific factor, or monetary policy impacting the private investment decision in India.

5 Conclusion

This paper examines the causes behind the sluggish private investment in India by taking advantage of the mixed-frequency VAR model. Our MF-VAR model consists of monthly short-term interest rate (SR), quarterly bank loans BL, firm profit π, and investment I. The classical VAR aggregates the monthly variables into a quarterly frequency which may lead to a loss of a certain degree of information. MF-VAR can combine variables of different frequencies. Mixed-frequency methodology thus allows us to examine the heterogeneous impact of monetary policy on investment. However, we find no substantial evidence of any impact of monetary policy on investment from both the classical and the MF-VAR analyses. We also fail to find any significant evidence of either the firm-specific variable or bank-specific variable impacting private investment in India. However, the mixed-frequency approach yields richer economic insights compared to the single-frequency approach. In future, we plan to further this investigation by incorporating variables such as economic policy uncertainty and stock prices to examine their heterogeneous impact on private investment in India.

References

Anand, R., & Tulin, V. (2014). Disentangling India's Investment Slowdown. Working Paper 14/47, International Monetary Fund, Washington, DC.

Anderson, B. D. O., Deistler, M., Felsenstein, E., Funovits, B., Koelbl, L., & Zamani, M. (2016). Multivariate AR systems and mixed frequency data: G-identifiability and estimation. *Econometric Theory, 32,* 793–826.

Andreou, E., Ghysels, E., & Kourtellos, A. (2010). Regression models with mixed sampling frequencies. *Journal of Econometrics, 158,* 246–261.

Barkbu, B., Berkmen, S. P., Lukyantsau, P., Saksonovs, S., & Schoelermann, H. (2015). Investment in the Euro Area: Why Has It Been Weak? International Monetary Fund Working Paper No. 15/32.

Bussière, M., Ferrara, L., & Milovich, J. (2015). Explaining the Recent Slump in Investment: The Role of Expected Demand and Uncertainty. Banque de France Working Paper No. 571.

Das, S., & Tulin, V. (2017). *Financial Frictions, Underinvestment, and Investment Composition: Evidence from Indian Corporates* (No. 17/134). International Monetary Fund.

Ghysels, E. (2016). Macroeconomics and the reality of mixed frequency data. *Journal of Econometrics, 193,* 294–314.

Ghysels, E., Hill, J. B., & Motegi, K. (2016). Testing for Granger causality with mixed frequency data. *Journal of Econometrics, 192,* 207–230.

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2004). The MIDAS Touch: Mixed Data Sampling Regression Models, Working Paper, UCLA and UNC.

International Monetary Fund (IMF). (2015, April). Private Investment: What's the Holdup? World Economic Outlook (pp. 111–143).

Lewis, C., Pain, N., Strásky, J., & Menkyna, F. (2014). Investment Gaps after the Crisis. OECD Economics Department Working Paper No. 1168.

Leboeuf, M., & Fay, R. (2016). What Is Behind the Weakness in Global Investment? Bank of Canada Staff Discussion Paper No. 2016-5.

McCracken, M. W., Owyang, M., & Sekhposyan, T. (2015). Real-Time Forecasting with a Large, Mixed Frequency, Bayesian VAR, No. 2015-030, FRB St Louis Paper.

Motegi, K., & Sadahiro, A. (2018). Sluggish private investment in Japan's Lost Decade: Mixed frequency vector autoregression approach. *The North American Journal of Economics and Finance, 43,* 118–128.

Motonishi, T., & Yoshikawa, H. (1999). Causes of the long stagnation of Japan during the 1990s: Financial or real? *Journal of the Japanese and International Economies, 13,* 181–200.

Saarenheimo, T. (1995). Credit crunch caused investment slump? An empirical analysis using Finnish data.

Sadahiro, A. (2005). *Sengo Nihon no Makuro Keizai Bunseki*. Tokyo: Toyo Keizai Inc.

Schembri, L. (2017, March 21). Getting Down to Business: Investment and the Economic Outlook. Remarks to the Greater Vancouver Board of Trade, Vancouver.

Silvestrini, A., & Veredas, D. (2008). Temporal aggregation of univariate and multivariate time series models: A survey. *Journal of Economic Surveys, 22,* 458–497.