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Forecasting Public Investment Using Daily Stock Returns☆

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Abstract

This paper investigates the predictability of public investment in Japan using the daily excess stock returns of the construction industry, to contribute to the recent discussion on fiscal foresight. To examine the relationship between monthly public investment and daily stock returns without any prior time aggregation, we employ the VAR model with MIDAS regression and estimate the optimal weights for connecting high-frequency and low-frequency data in addition to VAR coefficients and the variance-covariance structure. We find that the VAR model with MIDAS regression reduces the mean square prediction error in out-of-sample forecasting by approximately 15% and 2.5% compared to the no-change forecast and VAR model forecasting with prior time aggregation, respectively. Moreover, using the local projection method, we find evidence of the fiscal news shock estimated in our proposed model delaying positive effects on output, consumption, hours worked, and real wage when news shocks actually result in increasing public investment. This finding suggests the New Keynesian structure of the Japanese economy.

JEL classification: C22, C53, E62

Keywords: MIDAS regression, fiscal foresight, stock returns, local projection method.

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1. Introduction

Financial market variables contain much information to help forecast variations in macroeconomic data. Taking advantage of this desirable property of financial data, we investigate the predictability of public investment in Japan using the daily excess stock returns of the construction industry. This paper contributes to the recent discussion on fiscal foresight, where the focus is on fiscal policy foreseeability and to understand how it affects the economy (Mertens and Ravn, 2010; Leeper et al., 2012, 2013). That is, this paper tries to identify the series of fiscal news shocks and reveal their effect on macroeconomic variables by forecasting public investment using the daily stock returns of the construction industry. To achieve our purpose, we develop a model that directly connects monthly public investment with daily stock returns using mixed-frequency data.

The literature has been continually examining the effect of government spending and public investment shocks (hereinafter, fiscal policy shock), but there is little consensus on its macroeconomic effect. Two strands of time series analysis exist in the literature on the effect of fiscal policy, the VAR-based analysis conducted by Blanchard and Perotti (2002), Galí et al. (2007), and Mountford and Uhlig (2009), and the narrative approach adopted by Ramey and Shapiro (1998), Burnside et al. (2004), and Ramey (2011). The narrative approach mainly adopts war dummies to capture fiscal policy shock, because war is closely related to increases in government (military) spending. VAR analyses document the positive effects of government spending on consumption and real wage as well as output, while the narrative approach shows that fiscal policy shocks induce a decline in consumption and real wage. Ramey (2011) states that the two strands differ in the timing of identifying fiscal policy shock. Furthermore, the VAR approach might fail to capture the true timing of innovation because changes in government spending are anticipated before they actually occur owing to implementation lag. Following Ramey (2011), this paper focuses on fiscal news shocks to show the true effect of fiscal policy shock. Moreover, we need to understand its true effect in terms of evaluating the role of economic stimulus packages as well as distinguishing the competing macroeconomic models.

This paper considers the Japanese economy. The Japanese government implemented numerous fiscal stimulus packages after their bubble economy collapsed in the early 1990s and the 2007–08 global financial crisis. More recently, they adopted large-scale fiscal expansion policies as part of Prime Minister Abe's economic reforms, the so-called Abenomics; this included the reconstruction of Japan after the earthquake disaster. Therefore, we consider the Japanese economy a suitable subject for study in that it presents scores of fiscal events to be forecasted. In addition, the Japanese fiscal policy has been mainly analyzed using the VAR model, which does not consider fiscal foresight. Only a few recent studies have examined fiscal news shocks in Japan; for example, Fukuda and Yamada (2011), Morita (2017), Shioji (2017) and Kanazawa (2018). Thus, we consider it worthwhile to study the effect of fiscal news shocks in the Japanese economy.

This paper follows the method of Fisher and Peters (2011), who used the stock returns of large military contractors to identify the anticipated US military spending shocks. The method they used to identify fiscal news shocks could resolve the shortcomings of the narrative approach, where the number of fiscal innovations captured by war dummies are limited; they addressed this issue by extracting fiscal news shocks from time series of stock returns. The strategy of Fisher and Peters (2011) presumes that the financial market variables reflect almost all the current available information. Morita (2017) applies this method to the Japanese economy by replacing the military industry with the construction industry, because fiscal policy for economic stimulus is executed via public works in Japan.[1] Here, we need to purify fiscal news shocks from raw stock returns shocks because not all stock return variations are due to fiscal news shocks. Fisher and Peters (2011) propose the use of excess stock returns obtained by eliminating the market returns, while Morita (2017) uses the excess stock returns and then adopts the robust sign restriction method; fiscal news shocks are identified by imposing sign restrictions derived from the theoretical model.

The aforementioned studies consider the contamination of information in stock returns caused by factors other than fiscal news, but pay little attention to attenuate the information due to time aggregation of the data. Previous studies generally examine the effects of fiscal news shock on macroeconomic variable using the information of stock returns. Of course, stock returns is high-frequency data collected at (intra-)daily frequency, whereas the macroeconomic variables such as output and consumption are low-frequency data released at monthly or quarterly frequencies. If the data frequencies in the analysis are mixed, the high-frequency data (i.e., stock returns) will be normally integrated with the low-frequency data through time aggregation. In this case, the information originally contained in the high-frequency data might be discarded by such time aggregation, as pointed out in the forecasting literature (e.g., Ghysels et al., 2007). In particular, we can reasonably assume that such time aggregation of stock returns can dilute the information from noisy variation in stock returns. Hence, we use mixed frequency analysis to examine the relationship between monthly public investment and daily stock returns; this is

[1] Shioji (2017) and Kanazawa (2018) also use the stock returns of construction industry to identify the fiscal news shocks effect in Japan.

known as Mixed Data Sampling (MIDAS) regression.[2] MIDAS regression is widely accepted in oil price forecasting analysis using financial market variables (Baumeister et al., 2015) or nowcasting macroeconomic data (Foroni et al., 2015; Ghysels and Ozkan, 2015). To the best of our knowledge, few studies have used MIDAS regression to analyze macroeconomic policy; Francis et al. (2011) focus on the effect of monetary policy. Thus, this paper can be said to establish a novel method, at least in this literature, to refine fiscal shock from a different standpoint.

The outline of this paper is summarized as follows. We first examine the predictability of public investment using the construction industry's daily stock returns to check whether they can be considered as a proxy for fiscal news shocks. For this, we build the VAR model with MIDAS regression by including both monthly public investment and daily stock returns in a single VAR system. We then compare the mean square prediction error (MSPE) in the VAR model with MIDAS regression with those obtained from other possible models. We first confirm that the stock returns of construction industry can forecast a variation in public investment in the future, and then compute the impulse responses of some macroeconomic variables to fiscal news shock.

Our main finding in this study is that a variation in public investment is predicted by the stock returns of construction industry in Japan. The MIDAS specification significantly improves the predictability by as much as 2.5% compared to using time-aggregated monthly stock returns. We also find delayed positive responses of output, consumption, hours worked, and real wage to fiscal news shocks. This finding supports the evidence that the Japanese economy is consistent with the New Keynesian structure.

The remainder of this paper is structured as follows. Section 2 explains the structure and estimation method for VAR models with MIDAS regression employed in this paper. Section 3 presents our data description, with the empirical results presented in two parts: out-of-sample forecasting, and impulse responses of macroeconomic variables. Section 4 concludes the paper.

[2] An alternative procedure with mixed data frequency is the mixed-frequency(MF-) VAR model proposed by Schorheide and Song (2015). In this model, the unobserved high-frequency data originally published at low frequency are regarded as latent variables and estimated using the Kalman filter. In our case of relating monthly and daily data, however, we need to estimate a lot of latent variables because over twenty daily latent observations need to be estimated by the month. Moreover, Bai et al. (2013) document little to choose between MIDAS regression and the MF-VAR model for accuracy of predictability. Therefore, we adopt MIDAS regression in this paper.

2. Estimation model

2.1. VAR model with MIDAS regression

We first explain the VAR model with MIDAS regression; this allows us to directly deal with time series data sampled at different frequencies in a single VAR system. We then use a simple two-variable VAR model allowing for forecasting public investment using excess stock returns of the construction industry (hereinafter, stock returns).

Let y_t^M denote a vector of endogenous variables at monthly frequency consisting of public investment (g_t^M) and stock returns (er_t^M) in this order. The VAR system is written as

$$\begin{aligned} y_t^M &= \Phi_1 y_{t-1}^M + \cdots + \Phi_p y_{t-p}^M + u_t, \\ u_t &\sim N(0, \Sigma), \end{aligned} \tag{1}$$

where $\Phi_s (s = 1, \cdots, p)$ is a coefficient matrix with lag order s and Σ is a variance-covariance matrix for the reduced-form residuals vector denoted by u_t. Following MIDAS regression, we construct the monthly stock returns in the VAR system as a weighted average of daily returns as follows:

$$er_t^M = \sum_{j=1}^{d} \omega_j(\gamma_1, \gamma_2) er_{t,j-1}^D, \tag{2}$$

$$\omega_j(\gamma_1, \gamma_2) = \frac{\exp\left\{\gamma_1 j + \gamma_2 j^2\right\}}{\sum_{j=1}^{d} \exp\left\{\gamma_1 j + \gamma_2 j^2\right\}}, \tag{3}$$

where $er_{t,j-1}^D$ denotes the daily stock returns at the $j-1$st business day before the month-end t, and the form of weighting function $\omega_j(\gamma_1, \gamma_2)$ is the exponential Almon lag polynomial, as in Baumeister et al. (2015).[3] Note that MIDAS regression is a data-driven aggregation scheme because the shape of the weighting function is estimated using available information (Francis et al., 2011). In other words, the weights on daily stock returns are estimated to improve the fitness of the entire monthly VAR system, and hence er_t^M can be an appropriate monthly stock returns series in that they can be adjusted to explain the variation in endogenous variables better than the series obtained by way of an arithmetic average.

[3] Foroni et al. (2015) propose the unrestricted(U-) MIDAS regression, where the counterparts of eq. (2) are simply described as

$$er_t^M = \sum_{j=1}^{d} \alpha_j er_{t,j-1}^D.$$

Although this model can be conveniently estimated because of its linearity, the number of parameters to be estimated (i.e., α_j) will be relatively large in our case if we adopt U-MIDAS specification instead of the exponential Almon lag polynomial.

2.2. Bayesian inference

We define $X_t^M = I \otimes \left[y_{t-1}^M, \cdots, y_{t-p}^M\right]$ and $\Phi = [vec(\Phi_1)', \cdots, vec(\Phi_p)']'$, where the *vec* operator creates a column vector from $\Phi_s (s = 1, \cdots, p)$, by stacking the column vectors of Φ_s, and $\otimes$ denotes the Kronecker product. Then, eq. (1) can be rewritten as

$$\begin{aligned} y_t^M &= X_t^M \Phi + u_t, \\ u_t &\sim N(0, \Sigma). \end{aligned} \tag{4}$$

The parameters to be estimated here are summarized in $\Theta = [\Phi, \Sigma, \gamma_1, \gamma_2]$. We estimate these parameters using the random-walk Metropolis-Hastings (RW-MH) algorithm of the Bayesian Markov Chain Monte Carlo (MCMC) method. Since the RW-MH algorithm samples parameters by drawing candidates from the proposal distribution, we can estimate the VAR model with MIDAS regression relatively easily even with the nonlinearity in eq. (3). Given the data Y and prior distribution $\pi(\Theta)$, we sample from the posterior distribution $\pi(\Theta \mid Y)$ as follows:

1. Find the posterior mode $\hat{\Theta}$ of $\ln \pi(\Theta \mid Y)$.
2. Set $\Theta^{(0)} = \hat{\Theta}$ and $n = 1$.
3. Sample $\Theta^{(n)}_{\text{proposal}}$ from $\Theta^{(n)}_{\text{proposal}} = \Theta^{(n)} + \nu_t,\ \nu_t \sim N(0, cH)$.
4. Calculate the acceptance probability $q = \min\left[\frac{f\left(\Theta^{(n)}_{\text{proposal}} \mid Y\right)}{f\left(\Theta^{(n-1)} \mid Y\right)}, 1\right]$.
5. Accept $\Theta^{(n)}_{\text{proposal}}$ w.p. q and reject w.p. $1 - q$.
6. Set $\Theta^{(n)} = \Theta^{(n)}_{\text{proposal}}$ if it is accepted, and $\Theta^{(n)} = \Theta^{(n-1)}$ otherwise.
7. Return to step 3 until N iterations have been completed.

In the process above, N is set to $20,000$ and the initial $10,000$ samples are discarded as a burn-in. Also, H is the inverse of a Hessian matrix of $\ln \pi(\Theta \mid Y)$ multiplied by -1. We set $c = 2.38^2/q$, where q is the number of parameters in Θ, as proposed in Roberts and Rosenthal (2001).

2.3. Prior distributions

Our model is basically equal to a traditional VAR model, except for aggregating the daily data presented in eqs. (2) and (3). Therefore, we assume the prior distributions for Φ and Σ to be multivariate normal and inverse Wishart distributions; that is,

$$\Phi \mid \Sigma \sim N(\Phi_0, \Sigma \otimes \Omega_0),\ \ \Sigma \sim iW(\Sigma_0, k + 2). \tag{5}$$

Here, k is the number of endogenous variables in the VAR model ($k = 2$). As in Kadiyala and Karlsson (1997), the diagonal elements of Σ_0 are set to residual variances of the corresponding $p-$lag univariate autoregressions, while the diagonal elements of Ω_0 are constructed such that the prior variance of VAR coefficients on the s lagged j'th variables in the i'th equation equals

$\sigma_i^2/s\sigma_j^2$. These are set according to the Minnesota prior. Therefore, the coefficients attached to the first own lag in Φ_0 are set to unity, while the remaining coefficients are set to zero. As regards the priors for γ_1 and γ_2, we simply adopt the standard normal distribution given by

$$\gamma_i \sim N(0,1),\ \ i = 1,2. \tag{6}$$

In this setting, each observation of stock returns is presumed to be assigned equal weights in the prior (Ghysels, 2016).

3. Empirical results

3.1. Data and specification

In what follows, we show the empirical results of out-of-sample forecasting and the impulse responses of macroeconomic variables to public investment news shocks. Throughout the two exercises, the lag length in VAR model is set to two (i.e., $p = 2$) and the monthly stock returns in eq. (2) is constructed using the daily stock returns from the end of month to the twenty-fifth business day before the end of month (i.e., $d = 26$).[4] As for the data, the monthly series of public investment are taken from the *Quick Estimate of Construction Investment* published by the Ministry of Land, Infrastructure, Transport and Tourism in Japan. The public investment used here are a nominal series of construction work conducted by the government, defined as the sum of government building and government civil engineering work. The seasonality of the original series is eliminated by using X-12-ARIMA. The daily stock returns of the construction industry is calculated by taking the log differentials of closing price and multiplying them by 100. To control for the factors that might affect the stock prices of the construction industry other than fiscal news, we build the excess stock returns by subtracting the Nikkei average returns (market returns) from the construction industry returns. Moreover, the accumulated excess stock returns is employed in the estimation because of the noisy fluctuation in original excess stock returns, as pointed out in Fisher and Peters (2010).

In analyzing the macroeconomic effect of fiscal news shock, we focus on the impulse responses of consumption, hours worked, and real wage as well as output to find the macroeconomic models supported by the Japanese data. For monthly real consumption, we employ the index of consumption expenditure level obtained from the *Family Income and Expenditure Survey* published by the Ministry of Internal Affairs and Communication. This index is adjusted to control for the effects of difference in household size, number of days in the month, and changes

[4] All the daily data including in a month can be covered by tracking the daily data back to twenty-fifth business days from the end of month.

in price level. Thus, the index is a real series. The hours worked and real wage are obtained from the *Monthly Labor Survey* of the Ministry of Health, Labour and Welfare. The data source originally provided the average hours worked, employment, and real wage per worker for establishments with over five employees. We obtain the total hours worked by multiplying the hours worked by employment. We construct the hourly real wage by dividing the real wage by hours worked. For output, we employ indices of all industry activity (IAA) released by the Ministry of Economy, Trade and Industry as a proxy for output. As regards covering the construction, mining and manufacturing, and tertiary industry activities, the IAA is considered more suitable as a proxy of output rather than industrial production index, which captures only the mining and manufacturing activities. All the data employed here are seasonally adjusted in the data source.

3.2. Out-of-sample Forecasting

The total sample period in out-of-sample forecasting is from January 1987 to March 2017. This period is restricted by the data availability of public investment. For correspondence with this period, we use the daily stock returns from December 23, 1986, to March 31, 2017. For the April 2010 to March 2015 period (60 months), we recursively conduct 24 periods ahead out-of-sample forecasting. In other words, we repeat the estimation and forecasting by updating the estimation period on a monthly basis. That is, for initial estimation, we use the data from the beginning to March 2010 to forecast the April 2010 to March 2012 monthly data. Subsequently, we add the April 2010 data to the estimation and shift the forecasting period one month ahead for the second estimation. We iterate this process 60 times until the end of estimation period reaches to March 2015. Figure 1 displays the data for out-of-sample forecasting. The series of public investment is taken by a natural logarithm multiplying by 100. The shaded area corresponds to the forecasting period, which shows rapid increases in public investment stemming from the recovery from the Great East Japan Earthquake and fiscal expansion policies due to Prime Minister Abe's Abenomics.

[Figure 1 about here.]

To show the importance of information contained in daily stock returns in forecasting public investment, we calculate the MSPE of no-change forecast, the monthly AR and VAR models, and the VAR model with MIDAS regression. The monthly AR model includes the monthly public investment, while the monthly VAR model includes the monthly public investment and excess stock returns constructed using the month-end stock price only. That is, the difference between the monthly VAR model and the VAR model with MIDAS regression is whether the daily stock returns is assigned an optimal weight or not when they translate into monthly returns. The MSPE is computed at the $h-$period ahead forecasting as

$$MSPE(h) = \frac{1}{T_2 - T_1 + 1} \sum_{t=T_1}^{T_2} \left(\bar{\hat{y}}_{t+h} - y_{t+h} \right)^2, \tag{7}$$

where T_1 and T_2 correspond to April 2010 and March 2015, respectively. In addition, $\bar{\hat{y}}_{t+h} = \sum_{n=N_0+1}^{N} \hat{y}_{t+h}^{(n)}/(N - N_0)$, where $\hat{y}_{t+h}^{(n)}$ denotes the prediction value of public investment at $t + h$ calculated using the parameters drawn at the n-th MCMC iteration.

Following Baumeister and Kilian (2012) and Baumeister et al. (2015), we report the relative MSPE ratio to no-change forecast as well as the success ratio in Table 1. The success ratio indicates direction accuracy, and is defined as the proportion of forecasts correctly predicting the direction of change in public investment. The model is considered to perform well compared to no-change forecasting when the MSPE ratio takes a value less than unity, while the model forecast is considered reliable compared to the forecast using coin toss when the success ratio takes a value greater than 0.5. The significance of the MSPE ratio and success ratio is tested using the Diebold and Mariano (1995) test modified by Harvey et al. (1997) and the Pesaran and Timmermann (2009) test, respectively. Moreover, column (iv) in Table 1 shows the MSPE of the VAR model with MIDAS regression relative to the monthly VAR model to confirm the usefulness of MIDAS regression.

[Table 1 about here.]

From Table 1, the forecasts using the AR model shown at column (i) indicate lower MSPEs than the no-change forecasts throughout the horizon, with most of the success ratios below 0.5. However, the monthly VAR model and VAR model with MIDAS shown at columns (ii) and (iii), respectively, significantly improve the forecastability of public investment compared to the no-change forecast in terms of both the MSPE and success ratios. Thus, the stock returns of the construction industry contains information about a future variation in public investment, thus indicating that the construction industry stock returns can be regarded as a proxy for public investment news shock in Japan, as in Morita (2017) and Shioji (2017). The result also illustrates that the MPSEs derived from models using stock returns take the minimum values at around horizons eight and nine. The VAR model with MIDAS regression reduces the MPSE by about 15% at horizons eight and nine compared to no-change forecasting. The MSPE in the monthly VAR model also lowers by almost 12% at horizon eight. Similarly, the direction accuracy exceeds 0.5, with statistical significance at around horizon eight in both models. From these results, we can conjecture that the actual increase in public investment occurs at approximately eight or nine months after the news is announced.

Next, we consider the usefulness of daily data. Column (iv) in Table 1 displays the MSPE of the VAR model with MIDAS relative to the monthly VAR model. From the MSPE ratios in columns (ii) and (iii), the VAR model with MIDAS regression reduces the MSPEs by around 2.5% compared to the monthly VAR model for all horizons. Thus, the null hypothesis that the MSPE in the VAR model with MIDAS is greater than that in the monthly VAR model is rejected at the 10% significance level in horizons nine to twelve. Consequently, the stock returns of the construction industry is a good predictor for public investment, with its daily information improving the predictability of public investment even more than the monthly data.

3.3. Macroeconomic effects

The stock returns of the construction industry includes information about the future fiscal policy in the above exercise, and so we can examine the effects of fiscal news shock on macroeconomic variables. After estimating the VAR model with MIDAS regression, we can identify the fiscal news shock, denoted by v_t^{news}, from the reduced-form residuals u_t in eq. (1) through a recursive restriction as follows:

$$\begin{pmatrix} u_t^g \\ u_t^{er} \end{pmatrix} = \begin{pmatrix} a_{11} & 0 \\ a_{21} & a_{22} \end{pmatrix} \begin{pmatrix} v_t^g \\ v_t^{news} \end{pmatrix}. \tag{8}$$

Here, we adopt this identification presuming that the news cannot materialize in the same month. Another structural shock, denoted by v_t^g, is a surprising fiscal policy shock. We will not discuss this here.

As noted above, we analyze the effects on consumption, hours worked, real wage, and output, to detect a macroeconomic model supported by the data. This choice of variables is consistent with Fisher and Peters (2010) and Ramey (2011). Before introducing the method and result described here, we briefly review the prediction obtained from two theoretical models located in the opposite polar. First, the neoclassical model, as in Aiyagari et al. (1992) and Baxter and King (1993), shows that a government spending shock decreases consumption but increases the labor supply due to negative wealth effect, and the real wage then declines along with a fall in marginal productivity of labor.[5] In contrast, the New Keynesian model with the rule-of-thumb household, as in Galí et al. (2007), demonstrates that an increase in government spending raises the consumption, labor, and real wage. Therefore, the response of consumption and real wage is a key to distinguish the macroeconomic model.

[5]Strictly, public investment, which we consider in this paper, is different from government spending in terms of productivity, because public investment contributes to increase output by incorporating public capital at a future date. However, the model prediction mentioned here is qualitatively unchanged even when public capital has a productive effect, as in Baxter and King (1993).

To obtain the dynamic responses of each variable to fiscal news shock, we employ the local projection method proposed by Jordá (2005), instead of adding endogenous variables into the VAR model with MIDAS regression, because the value of the weights estimated in eq. (3) may also trace the variations in other variables besides public investment by incorporating additional variables into the VAR system. Another reason is the easiness to obtain the impulse responses, as pointed out in Ramey and Zubairy (2018). To obtain the impulse response function at horizon h, we estimate the single equation

$$\begin{gathered} x_{t+h} = \psi_h^1 z_{t-1} + \cdots + \psi_h^p z_{t-p} + \beta_h v_t^{news} + e_{t+h}, \\ e_{t+h} \sim N\left(0, \sigma_{v,h}^2\right), \end{gathered} \tag{9}$$

where x_t is a scalar of monthly macroeconomic variable of interest, and z_t is a vector of covariate including g_t^M, er_t^M, output, and x_t. In this specification, we can interpret the coefficient associated with v_t^{news}, represented as β_h, as the response of x at horizon h to the shock occurred at horizon 0. To calculate the dynamic responses, we estimate the above single equation for each horizon. In addition to the responses of consumption, hours worked, real wage, and output, we compute the responses of public investment and excess stock returns in the same manner. As regards the estimations for public investment and stock returns, we exclude x_t from z_t. We repeatedly estimate eq. (9) by changing h from 0 to 47 for each macroeconomic variable.[6]

We estimate the parameters in eq. (9) and Θ in eqs. (1) and (3) simultaneously using the Bayesian method as follows. First, we draw Θ as described in steps 1 to 6 in Subsection 2.2. We then extract the fiscal news shock v_t^{news} from the reduced-form residuals u_t which is calculated using the sampled Θ. Thereafter, we randomly draw $\Psi_h = [\psi_h^1, \cdots, \psi_h^p, \beta_h]'$, and $\sigma_{v,h}^2$, placing the calculated v_t^{news} on the right-hand side of eq. (9). For sampling simplicity, we set a conjugate prior distribution for Ψ_h and $\sigma_{v,h}^2$.[7] In short, we insert the sampling step for Ψ_h and $\sigma_{v,h}^2$ between steps 6 and 7 in the MCMC iteration shown in Subsection 2.2.

Figure 2 gives the data needed to examine the macroeconomic effects of fiscal news shock. Note that the sample period in this exercise is slightly different from the out-of-sample forecasting period. The sample period here is from January 1990 to March 2017 because the data for the labor market (i.e., hours worked and real wage) starts from January 1990. Similar to the out-of-sample forecasting analysis, all the data are taken by a natural logarithm multiplied by 100 and the estimation is carried out in level.

[Figure 2 about here.]

[6] However, to estimate the response of public investment, we set h from 1 to 47 because one can reasonably assume that fiscal news shock has no effect on public investment in the impact period.

[7] The prior and posterior distributions for Ψ_h and $\sigma_{v,h}^2$ are discussed in Appendix A.

The impulse responses of macroeconomic variables to fiscal news shocks are given in Figure 3. While the monthly responses of each variable are obtained in the estimation of eq.(9), Figure 3 is drawn by centering on the quarterly responses for the purpose of making it simply to interpret the results. This is because monthly responses are highly irregular presumably from the high-frequency fluctuation in the monthly data displayed in Figure 2. Quarterly responses are computed as the average of the monthly responses for every three months. In Figure 3, the quarterly and monthly median responses are depicted by a solid line with circles and a thin line, respectively, with the shaded area indicating 90% credible intervals corresponding to the quarterly responses. Since monthly responses are basically within the credible intervals, this transformation hardly changes the qualitative and quantitative interpretation of our results.

[Figure 3 about here.]

First, Figures 3(a) and (b) illustrate that fiscal news shocks involve a significant increase in public investment with a persistent positive effect on excess stock returns. These results confirm that stock returns of the construction industry is tied to a future public investment, as discussed in out-of-sample forecasting. Also, public investment exhibits a significant response around one year after a shock in accordance with the exposition of out-of-sample forecasting, where MSPEs are minimized at eight- or nine-months ahead forecasting.

Figures 3(c)–(f) exhibit a delayed significant positive effect of fiscal news shocks on output, consumption, hours worked, and real wage. As regards output and consumption, the responses are positive and significant for a few quarters after a significant increase in public investment.[8] Compared to output and consumption, hours worked takes some more quarters to become significant, while real wage becomes significantly positive before the fiscal news shock embodies as an actual change in public investment. From these results, we can conclude that an increase in public investment raises the output, consumption, hours worked, and real wage, although the time of significant increase depends on the variable. As regards distinguishing the macroeconomic model, the result clearly supports the New Keynesian model with some additional frictions (i.e., liquidity constraint and labor union), as proposed by Galí et al. (2007), for the Japanese economy. Moreover, our result emphasizes the role of fiscal policy as an economic stimulus package in that a fiscal news shock has a positive effect on consumption as well as output.

[8]Morita (2017) shows an immediate positive responses of consumption and output in contrast to our results, although both studies are similar in that consumption and output become positive when public investment increases. The difference in results suggests the possibility of too restrictive sign restriction based on theoretical prediction.

4. Conclusion

In order to obtain the fiscal news shock series and gauge their macroeconomic effects, we analyzed the predictability of public investment from the daily stock returns of the construction industry in Japan. To improve predictive accuracy, we used the proposed VAR model with MIDAS regression, connecting the monthly series of public investment with daily stock returns in a single VAR system. Moreover, we examined the effects of fiscal news shock on output, consumption, hours worked, and real wage based on the local projection method developed by Jordá (2005).

The results in out-of-sample forecasting clearly show that stock returns in the construction industry contains information about future changes in public investment. The models considering stock returns significantly improve the predictability of public investment. Moreover, the VAR model with MIDAS significantly reduces the MSPEs compared to a model using monthly data. Thus, this result suggests that simple time aggregation might deteriorate the quality of information contained in high-frequency data, as pointed out in Ghysels et al. (2007). The finding also shows that fiscal news shocks involve an actual increase in public investment about one year after the news is announced. This empirical fact contributes to specify the exogenous process of government spending in the theoretical analysis.

Our analysis of macroeconomic effects shows that Japanese data appear to support the New Keynesian framework. More precisely, we find that fiscal news shock has a significantly positive effect on output, consumption, hours worked, and real wage almost when the shock materializes an increase in public investment. Although the timing of the responses becoming significantly positive slightly differ between the variables, the responses are generally consistent with those derived from the ultra-Keynesian model, as presented in Galí et al. (2007). From the economic policy perspective, our findings also highlight the importance of fiscal policy as an economic stimulus package.

Finally, we suggest a foreseeable extension of this research. This paper has shown how to aggregate time series data using the proposed MIDAS model. However, sectoral stock price also constitutes aggregate data constructed from summing up the stock prices of individual firms. Therefore, the predictability of public investment can be further improved by aggregating the stock returns of each construction firm optimally. Also, cross-sectional aggregation might enable us to obtain fiscal news shocks series that are more clear than the ones presented in this paper. In a future work, we would like to develop a model where the stock returns can be integrated optimally in both time series and cross-sectional dimensions.

Appendix A. Estimation for the local projection method

Since eq. (9) is a linear regression model, we can rewrite it as the matrix representation of

$$X_h = W_h \Psi_h + e_h,\ e_h \sim N(0, \sigma_{v,h}^2 I_{T-p-h}), ; \tag{A.1}$$

here, $X_h = (x_{h+p+1}, \cdots, x_T)'$, and $W_h = (w'_{h+p+1}, \cdots, w'_T)'$, where $w_t = \left(z_{t-h-1}, \cdots, z_{t-h-p}, v_{t-h}^{news}\right)$, $e_h = (e_{h+p+1}, \cdots, e_T)'$, and T is the total number of observations. For the priors of Ψ_h and $\sigma_{v,h}^{-2}$, we set the Normal-Gamma conjugate priors specified as

$$\Psi_h \mid \sigma_{v,h}^2 \sim N(0, \sigma_{v,h}^{-2} I_m),\ \sigma_{v,h}^{-2} \sim Gamma\left(\frac{4}{2}, \frac{0.04}{2}\right),$$

where m is the number of coefficients included in Ψ_h. These priors lead to the posterior distributions as follows:

$$\sigma_{v,h}^{-2} \mid X_h \sim Gamma\left(\frac{4 + (T-p-h)}{2}, \frac{0.04 + e'e + \hat{\Psi}'_h W'_h W_h \hat{\Psi}_h - \tilde{\Psi}'_h M^{-1} \tilde{\Psi}}{2}\right),$$

$$\Psi_h \mid \sigma_{v,h}^2, X_h \sim N\left(M^{-1}\tilde{\Psi}_h, (\sigma_{v,h}^{-2} M)^{-1}\right),$$

where $\hat{\Psi}_h$ is an ordinary least squares (OLS) estimator of Ψ_h, $e = X_h - W_h \hat{\Psi}_h$, $M = I_m + W'_h W_h$, and $\tilde{\Psi}_h = W'_h W_h \hat{\Psi}_h$.

An important point to note here is that the posterior distribution of $\sigma_{v,h}^{-2}$ is conditional only on the data. In other words, the sampling for Ψ_h and $\sigma_{v,h}^{-2}$ can be proceeded without relying on the MCMC method, where parameter sampling is implemented using information from the previous iteration. Consequently, we can mitigate the computational burden for estimating our model, because the previous iteration values for the Ψ_h and $\sigma_{v,h}^{-2}$ need not be saved. Thus, we can easily incorporate the sampling for Ψ_h and $\sigma_{v,h}^{-2}$ into the VAR model estimation with MIDAS regression.

References

Aiyagari, R., Christiano, L. and Eichenbaum, M. (1992). The output, employment and interest rate effects of government consumption. *Journal of Monetary Economics*, 30(1), 73—86.

Bai, J., Ghysels, E. and Wright, J.H. (2013). State space models and MIDAS regressions. *Econometric Reviews*, 32(7), 779-813.

Baumeister, C., Guérin, P. and Kilian, L. (2015). Do high-frequency financial data help forecast oil prices? The MIDAS touch at work. *International Journal of Forecasting*, 31(2), 238-252.

Baumeister, C. and Kilian, L. (2012). Real-time forecasts of the real price of oil. *Journal of Business and Economic Statistics*, 30(2), 326-336.

Baxter, M. and King, R.G. (1993). Fiscal policy in general equilibrium, *American Economic Review*, 83(3), 315—334.

Blanchard, O.J. and Perotti, R. (2002). An empirical characterization of the dynamic effects of changes in government spending and taxes on output. *Quarterly Journal of Economics*, 117(4), 1329-1368.

Burnside, C., Eichenbaum, M. and Fisher, J., D.M. (2004). Fiscal shocks and their consequences. *Journal of Economic Theory*, 115(1), 89-117.

Diebold, F.X. and Mariano, R.S. (1995). Comparing predictive accuracy. *Journal of Business and Economic Statistics*, 13(3), 253-263.

Fisher, J., D.M. and Peters, R. (2010). Using stock returns to identify government spending shocks. *Economic Journal*, 120(544), 414-436.

Foroni, C., Marcellino, M. and Schumacher, C. (2015). Unrestricted mixed data sampling (MIDAS): MIDAS regression with unrestricted lag polynomials. *Journal of the Royal Statistical Society, Series A*, 178(1), 57-82.

Francis, N.R., Ghysels, E. and Owyang, M.T. (2011). The low-frequency impact of daily monetary policy shocks. Federal Reserve Bank of St. Louis Working paper Series 2011-009B.

Fukuda, S. and Yamada, J. (2011). Stock price targeting and fiscal deficit in Japan: Why did the fiscal deficit increase during Japan's lost decades? *Journal of the Japanese and International Economies*, 25(4), 447-464.

Galí, J., López-Salido, D. and Vallés, J. (2007). Understanding the effects of government spending on consumption. *Journal of the European Economic Association*, 5(1), 227-270.

Ghysels, E. (2016). Macroeconomics and the reality of mixed frequency data. *Journal of Econometrics*, 193(2), 294-314.

Ghysels, E., Sinko, A. and Valkanov, R. (2007). MIDAS regressions: Further results and new directions. *Econometric Reviews*, 26(1), 53-90.

Ghysels, E. and Ozkan, N. (2015). Real-time forecasting of the US federal government budget: A simple mixed frequency data regression approach. *International Journal of Forecasting*, 31(4), 1009-1020.

Harvey, D., Leybourne, S. and Newbold, P. (1997). Testing the equality of prediction mean squared errors. *International Journal of Forecasting*, 13(2), 281-291.

Jordá, Ó. (2005). Estimation and inference of impulse responses by local projections. *American Economic Review*, 95(1), 161-182.

Kadiyala, K.R. and Karlsson, S. (1997). Numerical methods for estimation and inference in Bayesian VAR-models. *Journal of Applied Econometrics*, 12(2), 99-132.

Kanazawa, N. (2018). The public invsetment multipliers: Evidence from stock returns of narrowly defined industry in Japan. Discussion Paper Series, Hitotsubashi Institute for Advanced Study, HIAS-E-66.

Lepper, E.M., Richter, A.W. and Walker, T.B. (2012). Quantitative effects of fiscal foresight. *American Economic Journal: Economic Policy*, 4(2), 115-144.

Lepper, E,M., Walker, T.B. and Yang, S-C.S. (2013). Fiscal foresight and information flows. *Econometrica*, 81(3), 1115-1145.

Mertens, K. and Ravn, M.O. (2010). Measuring the impact of fiscal policy in the face of anticipation: A structural VAR approach. *Economic Journal*, 120(544), 393-413.

Morita, H. (2017). Effects of anticipated fiscal policy shock on macroeconomic dynamics in Japan. *Japanese Economic Review*, 68(3), 364-393.

Mountford, A. and Uhlig, H. (2009). What are the effects of fiscal policy shock? *Journal of Applied Econometrics*, 24(6), 960-992.

Pesaran, M.H. and Timmermann, A. (2009). Testing dependence among serially correlated multicategory variables. *Journal of the American Statistical Association*, 104(485), 325-337.

Ramey, V.A. and Shapiro, M. (1998). Costly capital reallocation and the effects of government spending. *Carnegie Rochester Conference on Public Policy.*

Ramey, V.A. (2011). Identifying government spending shocks: It's all in the timing. *Quarterly Journal of Economics*, 126(1), 1-50.

Ramey, V.A. and Zubairy, S. (2018). Government spending multipliers in good times and in bad: Evidence from US historical data. *Journal of Political Economy*, 126(2), 850-901.

Roberts, G.O. and Rosenthal, J.S. (2001). Optimal scaling for various Metropolis-Hastings algorithms. *Statistical Science*, 16(4), 351-367.

Schorfheide, F. and Song, D. (2015). Real-time forecasting with a mixed-frequency VAR. *Journal of Business and Economic Statistics*, 33(3), 366-380.

Shioji, E. (2017). Extracting fiscal policy expectations from a cross section of daily stock returns. JSPS Grants-in-Aid for Scientific Research (S) Understanding Persistent Deflation in Japan Working Paper Series No.095.

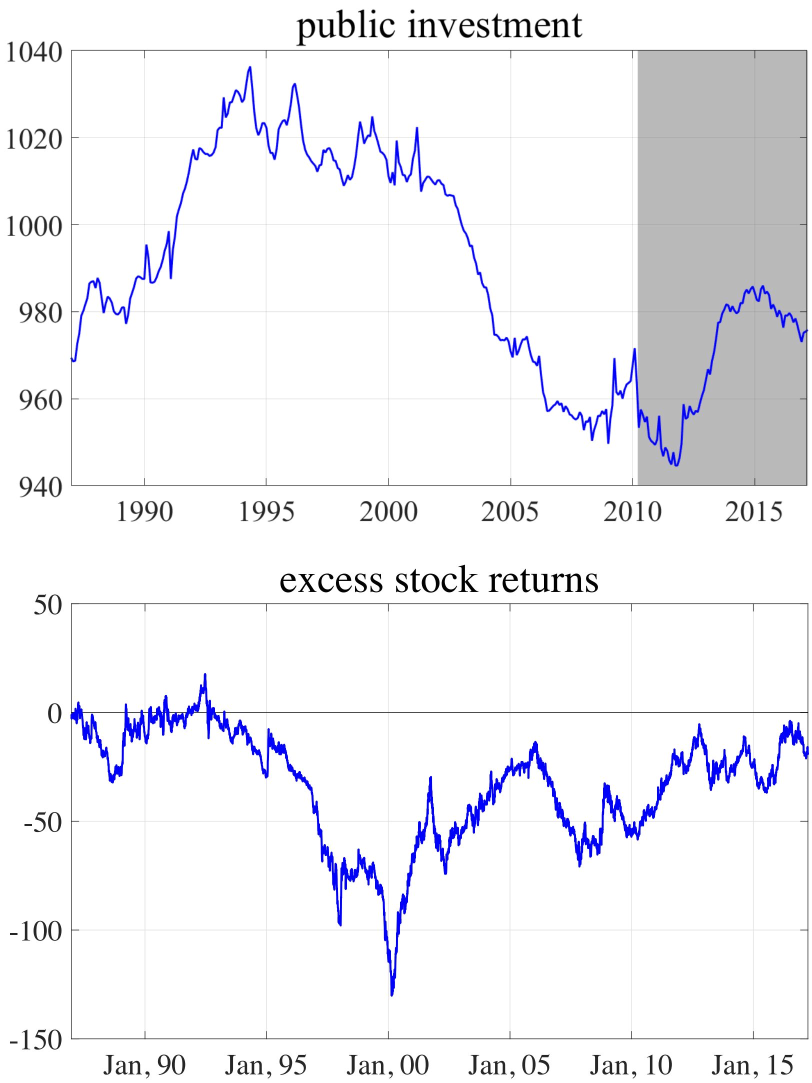

Figure 1: Data for out-of-sample forecasting

Notes: The figure shows the public investment (top) and excess stock returns time series of the construction industry (bottom) for the period from January 1987 to March 2017. Public investment are collected from the *Quick Estimate of Construction Investment*, and include the total government building and civil engineering investment. The data are seasonally adjusted by using X12-ARIMA and obtained by multiplying a natural logarithm by 100. The shaded area corresponds to the period from April 2010 to March 2015; this period is used for out-of-sample forecasting. The excess stock returns of the construction industry is obtained by subtracting the market returns from stock returns of the construction industry, computed using the daily closing price log differentials. Moreover, note that the data shown here relate to the accumulated excess stock returns.

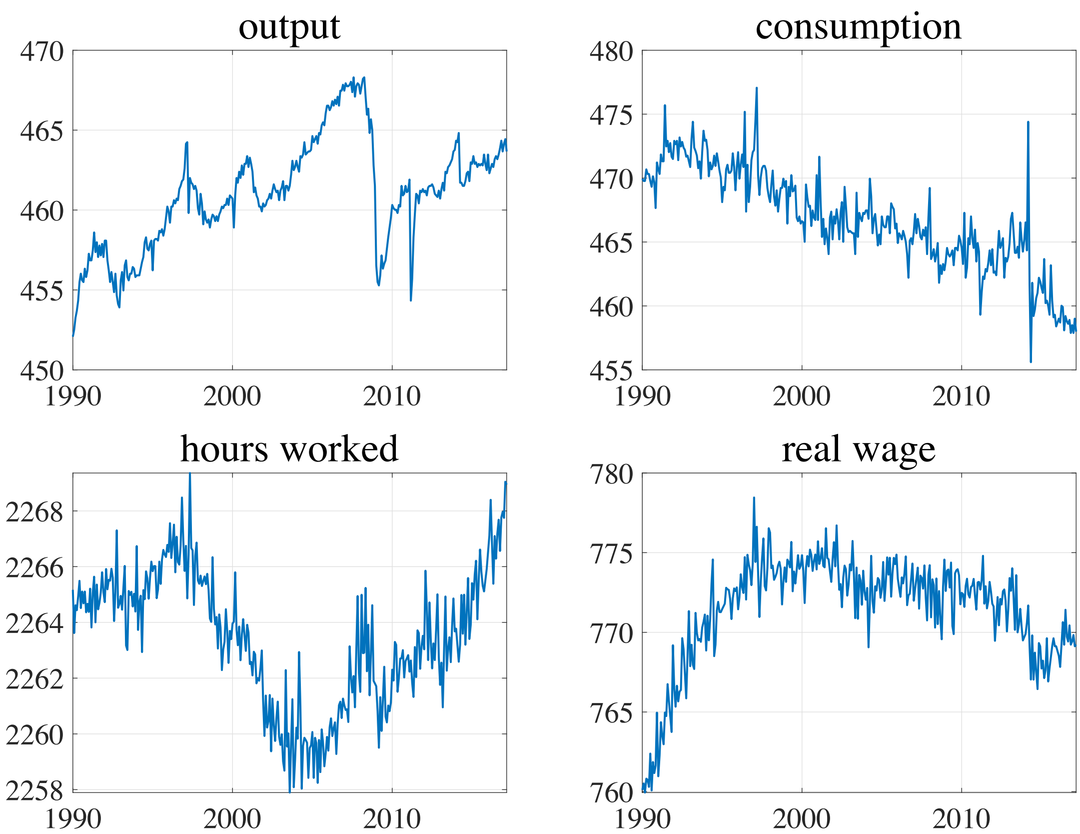

Figure 2: Data for analyzing the macroeconomic effects of fiscal news shocks

Notes: The sample period is from January 1990 to March 2017. All the data are seasonally adjusted series obtained by multiplying a natural logarithm by 100. Output is the *Indices of All Industry Activity* released by METI. Consumption is obtained from the *Family Income and Expenditure Survey*. Hours worked and real wage are collected from the *Monthly Labour Survey*. Hours worked are obtained by multiplying the total hours worked and regular employment, while the real wage give the hourly wage constructed by dividing the real wage by hours worked.

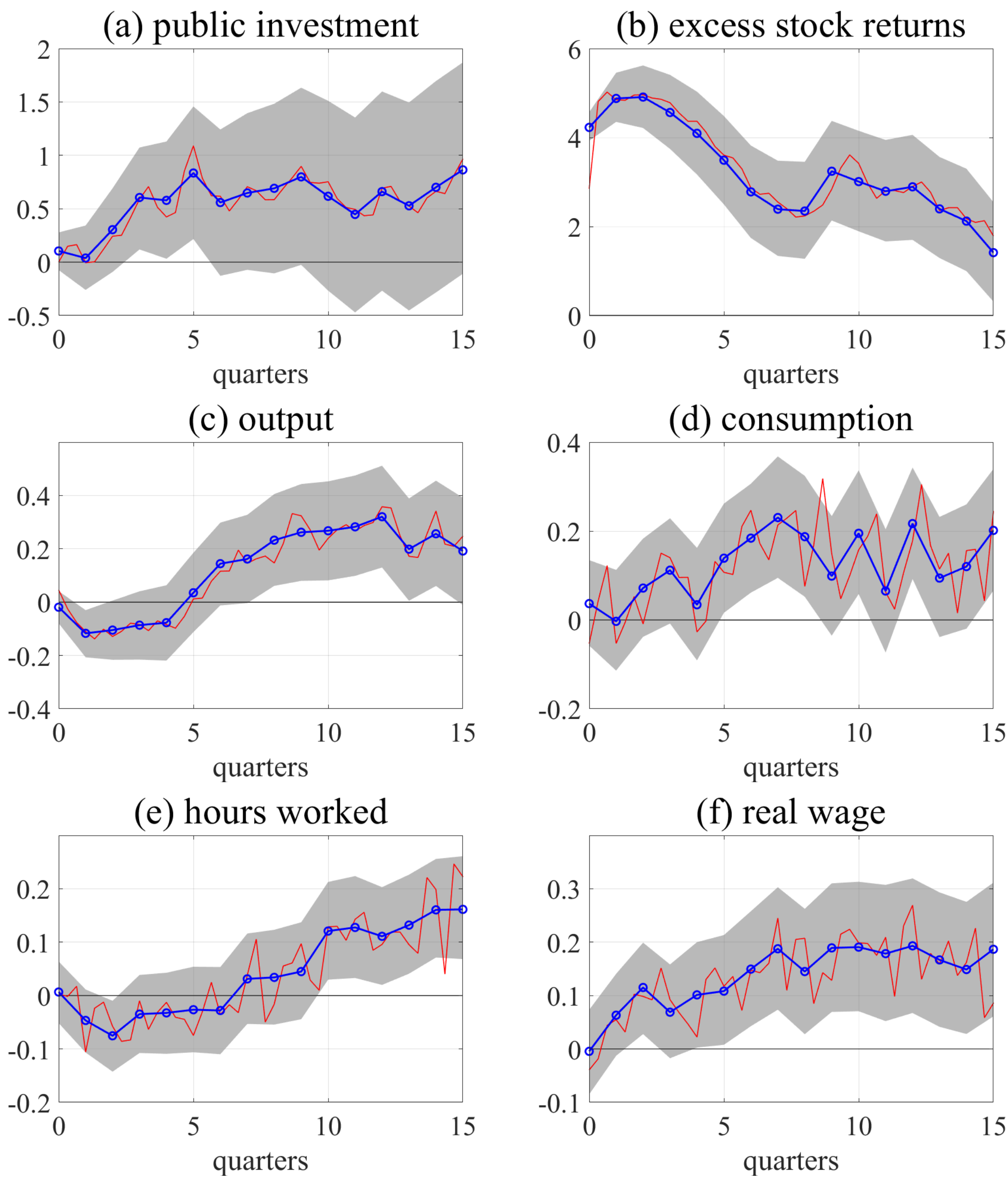

Figure 3: Impulse responses of macroeconomic variables to fiscal news shock

Notes: This figure shows the impulse responses of each variable to fiscal news shocks. Since the monthly responses, denoted by a thin line, appear highly irregular, the figure centers on the quarterly responses denoted by solid lines with circles. The quarterly response is computed as the average of the monthly responses for every three months. The shaded area indicates the 90% credible intervals corresponding to quarterly responses.

Table 1: Relative MSPE ratio

	Relative to no-change forecasting						to Monthly VAR
horizon	(i) Monthly AR		(ii) Monthly VAR		(iii) MIDAS VAR		(iv)MIDAS VAR
(months)	MSPE ratio	success ratio	MSPE ratio	success ratio	MSPE ratio	success ratio	MSPE ratio
1	1.033	**0.55**	1.010	**0.63**	1.003	**0.67****	**0.993**
2	1.029	0.48	**0.969***	**0.72****	**0.952****	**0.73****	**0.982**
3	1.024	**0.57**	**0.929****	**0.75****	**0.911****	**0.77****	**0.980**
4	1.030	**0.55**	**0.915****	**0.83****	**0.896****	**0.82****	**0.979**
5	1.033	0.48	**0.897****	**0.80****	**0.875****	**0.80****	**0.976**
6	1.041	**0.53**	**0.888****	**0.83****	**0.867****	**0.83****	**0.976**
7	1.047	0.48	**0.883****	**0.80****	**0.860***	**0.80****	**0.975**
8	1.055	**0.52**	**0.878***	**0.83****	**0.855***	**0.85****	**0.974**
9	1.061	**0.50**	**0.879***	**0.82****	**0.855***	**0.83****	**0.973***
10	1.068	0.43	**0.885**	**0.73****	**0.862**	**0.77****	**0.974***
11	1.071	0.47	**0.882**	**0.77****	**0.858**	**0.80****	**0.972***
12	1.076	0.42	**0.888**	**0.73****	**0.863**	**0.77****	**0.971***
15	1.095	0.33	**0.931**	**0.62**	**0.908**	**0.68***	**0.976**
18	1.113	0.28	**0.974**	**0.57**	**0.951**	**0.60**	**0.976**
21	1.134	0.18	1.014	0.47	**0.993**	**0.50**	**0.980**
24	1.148	0.12	1.048	0.40	1.030	0.43	**0.983**

Notes: The success ratio denotes the proportion of forecasts correctly predicting the direction of change in public investment. The null hypothesis that the prediction error in each model is greater than the error in no-change forecast is tested by the Diebold and Mariano (1995) test modified by Harvey et al. (1997). The direction accuracy is tested using the Pesaran and Timmermann (2009) test. In this table, ** and * indicate significance at the 5% and 10% levels, respectively.