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New Monthly Estimation Approach for Nowcasting GDP Growth: The Case of Japan*

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Abstract

This paper proposes a new approach for nowcasting as yet unavailable GDP growth by estimating monthly GDP growth with a large dataset. The model consists of two parts: (i) a few indicators that explain a large part of the variation in GDP growth, and (ii) principal components, which are orthogonal to those indicators and are extracted from a number of GDP source data, capturing the rest of the variation. The approach relies on a static factor model comprising a number of indicators that have a simultaneous relationship with GDP. Applying this approach to data for Japan, we find that our model produces more precise estimates of recent GDP growth at an earlier stage of nowcasting than the nowcasts of professional forecasters.

JEL Classification: C53, C82, E37

Keywords: Factor Models; Forecasting; Nowcasting; Monthly GDP; Real-time Data

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1 Introduction

Precise assessment of the current state of the economy is of key importance for the decision-making of economic agents. Among the various business cycle indicators, GDP growth is regarded as the most comprehensive one. In practice, however, we cannot rely solely on GDP growth to draw inferences on the current state of the economy. The reason is that GDP data are only available at a low frequency and with considerable delay. In the case of Japan, for example, the first Quarterly Estimate (QE) of GDP is released approximately one and half month after the end of the reference quarter. Moreover, since GDP data are calculated quarterly, they do not allow the analysis of economic developments at a higher frequency. Thus, it would be extremely useful if it were possible to observe GDP data in a more timely and frequent manner.

Against this background, recent years have seen efforts to develop methodologies for making short-term predictions of GDP with higher-frequency data, in other words "nowcasting" GDP.[1] In the past, the most common approach to nowcasting was the use of a system of single regression equations, often called bridge models; more recently, however, this has shifted to the estimation of dynamic factor models, which are based on a few common factors underlying a large number of economic indicators.[2] Recent studies on nowcasting indicate that dynamic factor models can track current economic growth well. Stock and Watson (2012), for example, show that their dynamic factor model can describe the economy around the financial crisis in the late 2000s.

The target horizon of nowcasting is not necessarily limited to the present period. Banbura et al. (2013) define nowcasting as the prediction of "the present, the very near future and the very recent past." Models for nowcasting GDP generally aim at better predictions for all three target horizons. Forecasts for the near future are likely to rely on financial variables and surveys, since these can be expected to reflect information on near-term economic activity. On the other hand, such indicators may be unnecessary if the focus is on the most recent quarter in the past. The reason is that in this case, unlike in the case of predictions for the present and later periods, it is not necessary to make guesses about future economic developments. When concurrent information on the quarter is available, the sole use of such information would be to increase the accuracy of predictions of GDP growth in the most recent period in the past. In this case, employing a static model would be appropriate, since timely indicators for the target quarter are expected to have a simultaneous relationship with GDP growth for the corresponding quarter.

This paper proposes a new approach for nowcasting as yet unavailable GDP growth by estimating monthly GDP growth with a large dataset. In the context of nowcasting, our model is a tool

[1] A comprehensive review of recent developments in nowcasting economic activity is provided by Banbura et al. (2013).

[2] Bridge models for nowcasting GDP are designed to estimate GDP growth through regression equations that rely on the relationship between GDP and a few higher-frequency indicators. An example is the model by Baffigi et al. (2004) for the euro area.

specifically designed to predict GDP growth in the recent past. Specifically, our approach provides early estimates of not-yet-published quarterly GDP growth by estimating monthly GDP growth. We construct a static factor model with a number of indicators that have a simultaneous relationship with GDP. In our data selection, we focus on the GDP source data for the target quarter. Since such data are ingredients of the official GDP statistics for the period, they should contain a broad range of concurrent information on GDP growth. We collect as much source data published monthly or quarterly and with a sufficiently short delay as possible. Consequently, our dataset mostly builds on the source data of the official GDP statistics.

Our model consists of two parts: (i) a few indicators that explain a large part of the variation in GDP growth, and (ii) principal components, which are extracted from a number of the GDP source data, capturing the rest of the variation. The principal components are based only on information in the source data orthogonal to the indicators that explain the largest part of the variation in GDP growth. A special feature of the model is that it categorizes the source data before extracting principal components from those data. Specifically, we divide GDP source data into several groups in terms of the information they provide, such as whether they focus on the demand side or the supply side. We find that grouping the data in this manner helps to improve the fit of the model.

Based on our new monthly estimation approach, we can produce monthly estimates of GDP growth at any time after the end of the month. Applying the methodology to data for Japan, we find that estimates of recent GDP growth provided by the approach are as accurate as those by professional forecasters two weeks before the release of the first QE. Moreover, for forecasts six weeks before the release of the first QE, the forecast error of our model is smaller than that of professional forecasters. This means that our model provides timely and relatively reliable estimates of GDP growth before the publication of the official GDP data.

The remainder of the paper is organized as follows. Section 2 introduces our dataset and describes how we estimate monthly GDP and nowcast the first QE. Section 3 reports estimation results of our model and monthly estimates of GDP growth produced by the model. In addition, we compare the performance of our model with that of professional forecasters. Section 4 applies our approach to producing nowcasts of the second QE. Section 5 concludes.

2 Methodology

2.1 Dataset

In Japan, the first QE of GDP is released nearly one and half month after the end of the reference quarter.[3] About three weeks after the first QE, the second QE is released, which provides an update

[3] In our analysis, we focus on GDP from the expenditure side, since GDP data based on the production and income approaches are available only on an annual basis.

of the GDP estimate. The second QE reflects updates of the GDP source data. As highlighted by Hara and Ichiue (2011), Japan has a long history of large and frequent revisions of its GDP data. Figure 1 plots the first, second, and final vintages of GDP. It is a matter of debate which of these vintages is of primary interest for agents. Earlier vintages provide a timely measure of economic activity, which agents can use for their decisions at the time. In contrast, later vintages should be a more accurate measure of economic developments. In this paper, we first focus on the first QE and then apply our method to nowcasting the second QE in Section 4. The reason for focusing on the earlier vintages of GDP is that this is what agents depend on for real-time decision-making.[4] This paper uses an updated version of the real-time GDP dataset initially collected by Hara and Ichiue (2011).[5]

The uniqueness of our dataset is that it provides a comprehensive collection of the source data of the QE, covering both demand-side and supply-side information. We choose 473 indicators from the QE source data, which are monthly or quarterly and become available with a three-month delay or less.[6] Table 1 lists the release dates of the major statistics in our dataset. The data in our dataset are as of January 31, 2013. All source data are in logarithmic first differences and seasonally adjusted.

Another feature of the dataset is that, aside from the source data, it contains the Index of Industrial Production (IIP), the Index of Tertiary Industries Activity (ITA), and 21 timely surveys. Our approach differs from typical nowcasting models for monthly GDP, which rely on a large number of timely indicators such as high-frequency financial data (e.g., Altissimo et al., 2010). Since our strategy is to mainly use the source data of the GDP statistics, the surveys are used only for the extrapolation of missing elements in the explanatory variables. The surveys in our dataset are the Markit/JMMA Japan Manufacturing PMI and the JP Morgan Global Manufacturing PMI, both provided by Bloomberg, and the Reuters Tankan by Thomson Reuters. The Reuters Tankan is a set of business sentiment indexes by industry.

2.2 Model Structure

This section outlines our method of estimating monthly GDP and nowcasting the first QE. Since monthly GDP is not available, we cannot directly estimate the monthly relationship between GDP and other indicators. Our approach therefore is to estimate the quarterly relationship between them and convert this to a monthly basis. We build a model designed to explain the largest part of GDP growth with a group of a few "main" indicators and the remainder of GDP growth with

[4] The framework we propose in this paper can also be applied for predicting the final vintage of GDP. In this case, we need the source data for all the revision stages from the first QE to the benchmark revision.

[5] To the best of our knowledge, there is no real-time dataset fully covering all the variables in our model. We leave it for future research to collect and utilize real-time data for all the variables.

[6] We rely on Cabinet Office (2006, 2012) for lists of the source data for the QEs.

a "supplemental" group of other indicators. We include the IIP and the ITA in the main group, since we assume that they represent economic activity in the manufacturing and services sectors, respectively. In practice, as we will show in Section 3, only two indicators can describe the largest part of GDP growth. The supplemental group consists of 473 of the data sources for the QEs of GDP.[7, 8]

It should be noted that not all series in our dataset have entries for the most recent month(s), since some data become available with a longer delay than others. In other words, the dataset shows a "jagged edge," which means we have an unbalanced panel. For example, going back to Table 1, the CGPI for a particular month becomes available within two weeks, while the balance of payments is released only six weeks after the end of the reference month. We need to fill in missing elements in each regressor to estimate monthly GDP, because we will later extract common patterns among many variables over the full sample. Specifically, we fill missing values in the IIP using the Survey of Production Forecasts for the current month and the Japanese PMI. The Survey of Production Forecasts for the current month is released together with the IIP for the preceding month as a supplementary indicator of the IIP. We extrapolate the rest of the variables using the extrapolated IIP, variables released earlier, and surveys. The Appendix explains our extrapolation method in detail.

The simplest way to estimate the model is to run a single regression of the first QE on all of the explanatory variables. In practice, however, indicators in the supplemental group are likely to be correlated with those in the main group. Moreover, too many regressors in one equation would cause the curse of dimensionality, so that the estimated equation would show poor performance. In order to deal with these problems, we take two steps. First, we exploit information from indicators in the supplemental group, which is orthogonal to the main group. Specifically, we estimate Equation (1) using OLS for each variable in the supplemental group:

$$x_{t,m}^{i} = \alpha_0^i + \alpha_1^i dlog\left(IIP_{t,m}\right) + \alpha_2^i dlog\left(ITA_{t,m}\right) + \varepsilon_{t,m}^{i}, \tag{1}$$

where $x_{t,m}^{i}$ is the i-th variable for the m-th month in quarter t. x is not transformed if it is usually used in a level form and is in first log difference form otherwise.

As a result, we have 473 residuals $(\varepsilon_{t,m}^{1}, ..., \varepsilon_{t,m}^{473})$, which capture economic fluctuations uncorrelated with the IIP and the ITA. The second step is to single out common patterns from the residuals. The key to exploiting information useful for nowcasting is to find a group of variables that contain

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[7] Nine out of the 473 sources are not for the first QE, but for the second QE. We use them nevertheless in this section, because the denominator of the GDP growth rate of the first QE is the second QE for the previous quarter.

[8] Each of the six quarterly sources in our dataset is converted to monthly data using a quadratic polynomial assuming that the quarterly level for each quarter matches the average level of the three months in the quarter. We leave the interpolation of these quarterly data using monthly indicators for future research.

similar information.[9] In this study, we categorize the 473 residuals into groups of demand- and supply-side data, following official statistics manuals for construction of the QE (Cabinet Office (2006, 2012)). The demand-side data group consists of four groups, namely (i) consumption, (ii) investment, (iii) international trade, and (iv) other demand-side data. The group consisting of other demand-side data covers GDP components with few source data, namely, housing investment, inventory investment, and government expenditure. Hence, we have one supply-side and four demand-side groups of the residuals. We extract six principal components from the residuals in each group.

Thus, we have all explanatory variables in our model to compute monthly GDP, namely the IIP, the ITA, and the set of the principal components. The quarterly nowcasting model to be estimated is:

$$y_t = \beta_0 + \beta_1 dlog\left(IIP_t\right) + \beta_2 dlog\left(ITA_t\right) + \beta_3 p^c_t + \beta_4 p^i_t + \beta_5 p^x_t + \beta_6 p^o_t + \beta_7 p^s_t + \eta_t, \qquad (2)$$

where y_t is the first QE of seasonally-adjusted quarter-on-quarter GDP growth for quarter t. The five principal components in the equation are p^c for the consumption factor, p^i for the investment factor, p^x for the international trade factor, p^o for the factor extracted from other demand-side data, and p^s for the supply-side factor. Since we have six principal components for each of the five groups, we have 6^5 combinations of p^c, p^i, p^x, p^o, and p^s. We choose the combination which minimizes the AIC (Akaike Information Criterion) when regressing Equation (2).[10, 11] As mentioned in Section 1, our model is static. Hence, we never use information not directly related to the reference month or quarter. For example, the nowcast for 2012Q4 depends on data for October, November, and December 2012.

Converting the estimated Equation (2) to a monthly basis, we obtain the model to estimate monthly GDP. Following the approximation method proposed by Mariano and Murasawa (2003), we approximate the quarter-on-quarter growth rate using three-month growth rates as follows:

$$y_t \simeq \frac{1}{3}\left(z_{t,1} + z_{t,2} + z_{t,3}\right), \qquad (3)$$

[9] Boivin and Ng (2006) show that factors taken from a large dataset can generate worse forecasts than those from its subset. They also point out that properties of the data should be considered for forecasting with factors.

[10] Conventional information criteria, such as the AIC and BIC (Bayesian Information Criterion), presume that regressors are observed. Factors, however, are not observed but estimated. Thus, for factor models, estimation error in factors could affect model selection based on these conventional information criteria. A growing strand of research is modifying conventional information criteria taking account of factor estimation error. A recent example is the study by Groen and Kapetanios (2013). They suggest modified versions of the BIC and the Hannan-Quinn Information Criterion that are generally applicable for factor models.

[11] The third principal component is chosen in the case of the supply-side group, while the first principal component is chosen in each case of the other groups.

where

$$\begin{aligned} z_{t,1} &= y_{t-1,2} + y_{t-1,3} + y_{t,1}, \\ z_{t,2} &= y_{t-1,3} + y_{t,1} + y_{t,2}, \\ z_{t,3} &= y_{t,1} + y_{t,2} + y_{t,3}, \end{aligned}$$

where $y_{t,m}$ and $z_{t,m}$ are the monthly and three-month growth rates for the m-th month in quarter t, respectively. With the approximation, the model for monthly GDP is written as:

$$\hat{y}_{t,m} = \frac{1}{3}\hat{\beta}_0 + \hat{\beta}_1 dlog\left(IIP_{t,m}\right) + \hat{\beta}_2 dlog\left(ITA_{t,m}\right) + \hat{\beta}_3 p^c_{t,m} + \hat{\beta}_4 p^i_{t,m} + \hat{\beta}_5 p^x_{t,m} + \hat{\beta}_6 p^o_{t,m} + \hat{\beta}_7 p^s_{t,m}, \quad (4)$$

where coefficients with hats are estimates.[12] $\hat{y}_{t,m}$ is an estimate of the monthly growth rate for the m-th month in quarter t.

Finally, we obtain the nowcast for the first QE by simply substituting Equation (4) into (3):

$$\hat{y}_t = \frac{1}{3}\left(\hat{z}_{t,1} + \hat{z}_{t,2} + \hat{z}_{t,3}\right). \quad (5)$$

We can calculate monthly GDP growth from the end of the month, when the two surveys used to extrapolate IIP become available. We can also compute early estimates of quarterly GDP from the end of the third month, when monthly GDP estimates for the three months in a quarter become available.

3 Estimation Results

The estimation results of the quarterly nowcasting model using data for Japan are presented in Table 2. The observation period is 2004Q4, the start of the chain-based first QE, to 2012Q3. As can be seen in Table 2(a), with an adjusted R^2 of 0.921, the model shows a good within-sample fit. The use of principal components improves the fit of the model, since the model without them has a lower adjusted R^2 of 0.838. On the other hand, if we use the five principal components from all the data sources without grouping them, the adjusted R^2 of the estimated model falls to 0.819. The case of the lowest AIC without data grouping, in which only the third principal component of the five is selected, has an adjusted R^2 of 0.841. This result indicates that data grouping in the extraction of principal components improves the within-sample fit of our model.

Next, Figure 2 plots the official first QE against our estimates. The figure shows that our method tracks the first QE very well. The model captures rapid changes in economic growth, such as around the Lehman shock in 2008 and after the major earthquake that hit eastern Japan in

[12] The intercept in Equation (4) is one-third of $\hat{\beta}_0$, because $\hat{\beta}_0$ represents the three-month growth rate.

March 2011. Breaking down the fit, we find that the principal components extracted from the source data, as well as the IIP and ITA, make a large contribution to explaining the fit of the first QE. This implies that along with the IIP and ITA, the two major indexes for gauging the business cycle in Japan, the source data are quite informative in predicting GDP.

Figure 3 depicts monthly, three-month, and rolling quarterly estimates of GDP growth. Based on Equation (3), the rolling quarterly estimate can be obtained as the three-month average of the three-month sum of GDP growth. In the third month of every quarter, the rolling quarterly estimates match the quarterly estimates of the first QE for the quarter. While the monthly estimates are volatile, the rolling quarterly estimates fluctuate less, which may be helpful for a more precise assessment of the state of the economy.

The monthly GDP estimates provide tentative estimates for the current quarter even before the quarter ends. Figure 4 shows monthly estimates of quarterly GDP growth for every month from January 2012 to January 2013. The estimate in the first month within a particular quarter is the quarterly growth rate if the level of monthly GDP registered in the first month remained unchanged over the next two months. The second-month estimate is the quarterly growth rate if the level of monthly GDP in the third month was equivalent to the average of the first two months. The third-month estimate is equal to the estimate for the quarter. In practice, we cannot directly evaluate the accuracy of our monthly estimates, because no official monthly GDP statistics are available. Nevertheless, the good within-sample fit of the quarterly nowcasting model suggests that the model well describes monthly economic growth.

Next, we compare our nowcasts of the past-quarter first QE with those of professional forecasters, which are made six and two weeks before the first QE is released. Six weeks ahead of the release date is at the end of the reference quarter, when the two surveys for the IIP extrapolation are released. Two weeks before the release of the first QE is when the actual IIP of the third month of the reference quarter becomes available. We use the ESP Forecast (ESP) as a proxy of real-time averaged nowcasts of professional forecasters. The ESP, published by the Japan Center for Economic Research, collects about 40 professional forecasters' nowcasts of the first QE around the end of the first and second months in a quarter.[13] To compare the performance of our nowcasts and those of the ESP, we calculate the Root Mean Squared Error (RMSE) over the observation period of 2004Q4 to 2012Q4.

Figure 5 shows the forecast errors of our nowcasts and the ESP, while Table 3 summarizes the

[13] To compare our nowcasts and the real-time professional nowcasts, we should conduct real-time nowcasts by estimating the model using information available only at real-time. Thus, we should use a real-time dataset for all the variables over the real-time observation period. However, we cannot conduct such real-time estimations, since there is no real-time database covering all the indicators we use, and the real-time observation period is too short to obtain reliable parameter estimates. As an alternative, we built a dataset for each quarter in the observation period which is designed to replicate the real-time data availability of our original dataset. The dataset for the particular quarter has the typical pattern of publication lags of the indicators in our model six or two weeks before the release of the first QE for the quarter.

RMSEs. Six weeks before the release of the first QE, our model has an RMSE of 0.39 percentage points, which is much lower than the 0.60 percentage points of the ESP. One month later, our model records an RMSE of 0.34 percentage points, which is quite close to the 0.33 percentage points of the ESP. These results indicate that our model can predict the first QE with higher precision than professional forecasters as soon as the reference quarter ends, and even at the end of the reference quarter, the model performs almost as well as one month later.

4 An Application: A Model for the Second QE

This section applies our nowcasting approach to the estimation of the second QE.[14] In this case, we need to predict revisions between the first and second QEs. Since the second QE can be described as the first QE plus a news component, which becomes available after the first QE is released. If this is the case, the revision should have mean zero and be orthogonal to the first QE. This means that $\kappa_0 = \kappa_1 = 0$ in the following equation:

$$g_t = \kappa_0 + \kappa_1 y_t + e_t, \tag{6}$$

where g_t is the revision to GDP in quarter t from the first to the second QE. Estimating Equation (6) over the observation period of 2004Q4 to 2012Q3, we find that the joint null hypothesis of $\kappa_0 = \kappa_1 = 0$ is not rejected.[15] This suggests that the revision at this stage is news. If we can precisely predict the news by using new information in the source data of the second QE, this would result in an accurate nowcast for the second QE. We therefore construct a model for the revisions between the first and the second QE.

The main group of explanatory variables consists of corporate investment data released by the Ministry of Finance as well as the IIP and the ITA. Corporate investment is assumed to be the largest contributor of GDP revisions among the source data added to the second QE. The supplemental group of variables comprises the source data for the second QE, including those already used in the first QE. We utilize the source data for the first QE because any revision to those data will be incorporated in the second QE. The newly-added source data consists of three groups, namely, (i) private investment, (ii) other demand-side data, and (iii) supply-side data. We divide the rest of the source data into the same five groups as in Section 2. We extract three principal components

[14] We do not construct a model for monthly GDP in this section, because the majority of the source data added at this stage of revision are quarterly. However, we could convert quarterly source data into monthly series using interpolation and compute monthly GDP based on the second QE as well.

[15] This test is employed by Faust et al. (2005), who examine the predictability of GDP revisions in the G-7 countries up to the late 1990s.

from each group. Our nowcasting model for the second QE is written as:

$$\begin{aligned} g_t &= \rho_0 + \rho_1 dlog\left(INV_t\right) + \rho_2 dlog\left(IIP_t\right) + \rho_3 dlog\left(ITA_t\right) \\ &\quad + \rho_4 q_t^i + \rho_5 q_t^o + \rho_6 q_t^s + \rho_7 p_t^c + \rho_8 p_t^i + \rho_9 p_t^x + \rho_{10} p_t^o + \rho_{11} p_t^s + \zeta_t, \end{aligned} \tag{7}$$

where INV denotes quarterly corporate investment. The three principal components taken from the newly-added source data are q^i for the investment factor, q^o for the factor extracted from other demand-side data, and q^s for the supply-side factor. These principal components are collected by choosing one from each group based on the AIC.

We estimate Equation (7) by OLS. The observation period is from 2004Q4, when the chain-based second QE started, to 2012Q3. Table 4 presents the estimation results of the model. The estimated model has a good within-sample fit with an adjusted R^2 of 0.70. Figure 6 shows that the official second QE and the fitted values of the model move very closely. The figure also shows that corporate investment accounts for a substantial part of the revision. This is consistent with the fact that estimates of private investment are substantially revised between the first and the second QEs.

As in Section 3, we compare the performance of the past-quarter second QE of our model with the performance of professional forecasters' nowcasts. Figure 7 plots the forecast errors of our model and those of professional forecasters' nowcasts, while Table 5 presents the RMSEs. As for the nowcasts of professional forecasters, we use the average of the nowcasts of professional forecasters which become available a week before the second QE is released, just after the release of the corporate investment data. Specifically, we use roughly ten professional nowcasts for the second QE, which are mainly from the Nikkei.[16] Table 5 shows that our model for the second QE has an RMSE of 0.12 percentage points, which is lower than the 0.19 percentage points of professional forecasters' nowcasts. Figure 7 shows that in absolute terms the largest forecast error of the model is 0.3 percentage points, which is less than the 0.4 percentage points of that of professional forecasters. These results imply that our model for the second QE can produce more precise nowcasts than professional forecasters.

5 Conclusion

For economic agents who need to make decisions in real-time, precise and timely assessment of the current state of the economy is of key importance. In this study, we proposed a new nowcasting approach designed to track recent economic growth by estimating monthly GDP with a large dataset. In particular, our approach provides early estimates of not-yet-published quarterly GDP

[16] If we cannot find any relevant nowcasts in the Nikkei, we alternatively collect those from the Bloomberg.

growth by estimating monthly GDP growth. We construct a static factor model with a large number of GDP sources containing a broad range of simultaneous information on GDP growth. The approach consists of two parts: (i) a few indicators that explain a large part of the variation in GDP growth, and (ii) principal components, which are orthogonal to those indicators and are extracted from a number of GDP sources, capturing the rest of the variation. A special feature of the model is that it categorizes the source data before extracting principal components from those data. Applying this methodology to data for Japan, we find that estimates of recent GDP growth provided by the approach are as accurate as those by professional forecasters two weeks before the release of the first QE. Moreover, for forecasts six weeks before the release of the first QE, the forecast error of our model is smaller than that of professional forecasters. Further, the estimation results for our model indicate that data grouping helps to greatly improve the fit of the model.

Our nowcasting approach is a simple and practical tool for the timely assessment of the economy. We expect that our framework will have various applications. For example, it could be applied to nowcasting GDP growth in other countries, if sufficient source data for GDP are available. We leave further applications for future research.

Appendix: Method of Extrapolation

We begin with a dataset in which indicators have different publication lags. Our extrapolation method consists of two steps. The first step is to extrapolate the variables in the main group introduced in Section 2, namely, the IIP and the ITA. The equation to extrapolate the IIP has two timely surveys as regressors, namely the Survey of Production Forecasts for the current month and the Japanese PMI. The extrapolation equation is:

$$dlog\left(IIP_{t,m}\right) = \gamma_0 + \gamma_1 dlog\left(IIPX_{t,m}\right) + \gamma_2 dlog\left(PMI_{t,m}\right) + \varsigma_{t,m}, \tag{A1}$$

where $IIPX_{t,m}$ and $PMI_{t,m}$ are the Survey of Production Forecasts for the current month and the Japanese PMI for the m-th month in quarter t, respectively. We estimate this equation over the observation period of February 2003 to December 2012.[17] The estimated equation has a good within-sample fit with an adjusted R^2 of 0.86. We extrapolate the IIP in the most recent month by predicting it with the estimated Equation (A1).

On the other hand, it is difficult to find any specific indicator that sufficiently explains the ITA. Since our nowcasting model introduced in Section 2 is static, it is desirable not to rely on lagged information to extrapolate the ITA. To extrapolate the ITA, we therefore use the IIP, surveys, and a number of the sources for the QEs of GDP, which we assume to have a simultaneous relationship with GDP. In order to collect information orthogonal to the IIP in each of the sources and surveys, we estimate the following equation for the i-th monthly indicator, x^i:

$$x^i_{t,m} = \alpha^i_0 + \alpha^i_1 dlog\left(IIP_{t,m}\right) + \nu^i_{t,m}. \tag{A2}$$

Equation (A2) is similar to Equation (1), but does not include the ITA on the right-hand side. The resulting residuals contain some economic activity which the IIP cannot explain. The observation period is February 2002 to December 2012.[18] The extrapolation equation for the ITA is:

$$dlog\left(ITA_{t,m}\right) = \chi_0 + \chi_1 dlog\left(IIP_{t,m}\right) + \chi_2 r_{t,m} + \varphi_{t,m}, \tag{A3}$$

where $r_{t,m}$ is a principal component extracted from the residuals which we obtained by estimating Equation (A2) for each of the sources and surveys.

In practice, many of the sources have to be extrapolated ahead of extrapolating the ITA. We fill in the missing values for each source using this method with Equations (A2) and (A3). In this case, $r_{t,m}$ in Equation (A3) is based on the residuals of estimating Equation (A2) for the surveys

[17] The Survey of Production Forecasts for the current month with a base-year of 2005 is available from January 2003 onward. Since we take the log difference between the Production Forecasts and the IIP for the last month, the observation period starts in February 2003.

[18] More than 95 percent of the source data in our dataset have entries for January 2002.

and sources released earlier than the variable, x^i. We label the extrapolation for each source at this stage as "informal," because the filled elements for each indicator do not reflect any information in the ITA.

The second step is to extrapolate each source in the supplemental group with the IIP, the ITA, surveys, and the source data released earlier than the indicator. The IIP and the ITA to be used have been extrapolated in the first step. Equation (A4) is a modification of Equation (A2) taking account of information in the ITA:

$$x_{t,m}^i = \mu_0^i + \mu_1^i dlog\left(IIP_{t,m}\right) + \mu_2^i dlog\left(ITA_{t,m}\right) + \xi_{t,m}^i. \tag{A4}$$

Estimating this equation for a variable x^i, we obtain a residual reflecting economic activity uncorrelated with the IIP and the ITA. The "formal" extrapolation equation for a variable x^i is:

$$x_{t,m}^i = \theta_0^i + \theta_1^i dlog\left(IIP_{t,m}\right) + \theta_2^i dlog\left(ITA_{t,m}\right) + \theta_3^i s_{t,m} + \psi_{t,m}^i, \tag{A5}$$

where $s_{t,m}$ is a principal component extracted from the set of the residuals computed by estimating Equation (A4). We fill in missing elements for each source by predicting them with the estimated Equation (A5). We apply this extrapolation recursively from indicators with the shortest delay to those with the longest delay. This is how we obtain a balanced panel data up to the most recent month.

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Table 1: Release Dates of Major Statistics in Our Dataset

	Statistics	Delay (Approx.)
GDP source data: Supply side		
	CGPI	2 weeks
	Industrial Production (Production and Shipments)	1 month
	Current Survey of Commerce	1 month
	Monthly Labour Survey	1 month
	Labour Force Survey	1 month
	Current Survey of Selected Service Industries	5 weeks
	Current Survey of Production	1.5 months
GDP source data: Demand side		
	Trade Statistics	3 weeks
	Family Income and Expenditure Survey	1 month
	Industrial Production (Inventories)	1 month
	Building Starts	1 month
	CPI	1 month
	Balance of Payments	5 weeks
	Survey of Household Economy	2.5 months
Business surveys		
	Markit/JMMA Japan Manufacturing PMI	0 days
	JP Morgan Global Manufacturing PMI	1 day
	Reuters Tankan	3 weeks

Note: This table shows the first release dates of major statistics in our dataset. The delay of the Markit/JMMA Japan Manufacturing PMI is 0 days, since it is released at the end of the reference month.

Table 2: Estimation Results of Nowcasting Model for the First QE

(a) Principal Components with Data Grouping

Variable		Coefficient		(Without principal components)	
Constant	β_0	0.002	(3.119)	0.002	(2.476)
dlog(IIP)	β_1	0.147	(8.730)	0.132	(6.234)
dlog(ITA)	β_2	0.491	(3.491)	0.488	(3.163)
Principal components					
Consumption	β_3	0.0013	(2.165)		
Investment	β_4	-0.0008	(-3.907)		
International trade	β_5	-0.0008	(-1.819)		
Other demand-side	β_6	0.0008	(1.893)		
Supply-side	β_7	0.0007	(2.897)		
	Adj. R^2	0.921		0.838	
	D.W.	2.503		2.857	

(b) Principal Components without Data Grouping

Variable		Up to fifth component		Lowest AIC	
Constant		0.002	(2.206)	0.002	(2.468)
dlog(IIP)		0.148	(4.295)	0.128	(6.003)
dlog(ITA)		0.504	(2.745)	0.459	(2.965)
Principal components					
First principal component		0.0003	(0.672)		
Second		-0.0003	(-0.737)		
Third		0.0004	(1.101)	0.0003	(1.212)
Fourth		-0.0001	(-0.298)		
Fifth		-0.0001	(-0.343)		
	Adj. R^2	0.819		0.841	
	D.W.	2.824		2.820	

Note: All the estimations in Table 2 take the first Quarterly Estimates of real GDP growth as the dependent variable. The observation period is 2004Q4 to 2012Q3. *t*-values are in parentheses. Panel (a) reports the results of the estimations with and without principal components. We apply data grouping to the estimation with principal components. Panel (b) shows the estimation results without data grouping. The second and third columns of (b) report the results of the estimation using the five principal components extracted from all the GDP sources in our dataset. The fourth and fifth columns of (b) report the results of the estimation in which we choose the combination of these five principal components which minimizes the AIC. In this case, only the third principal component is selected.

Table 3: Root Mean Squared Errors for the First QE

	Our approach	ESP Forecast
Six weeks before the release date	0.39	0.60
Two weeks before the release date	0.34	0.33

Note: Table 3 uses the ESP Forecast results collected around the end of the first month of each quarter. The observation period for the RMSEs in this table is from 2004Q4 to 2012Q4.

Source: ESP Forecast, Japan Center for Economic Research.

Table 4: Estimation Result of Nowcasting Model for the Second QE

Variable		Coefficient	
Constant	ρ_0	-0.000	(-0.560)
dlog(Corporate investment)	ρ_1	0.035	(5.136)
dlog(IIP)	ρ_2	-0.029	(-4.337)
dlog(ITA)	ρ_3	0.060	(1.102)
Principal components			
From the source data for the first QE			
Consumption	ρ_4	0.0003	(2.006)
Investment	ρ_5	-0.0010	(-3.415)
International trade	ρ_6	-0.0006	(-2.778)
Other demand-side	ρ_7	0.0004	(1.978)
Supply-side	ρ_8	0.0001	(2.043)
From the source data added for the second QE			
Investment	ρ_9	0.0005	(1.672)
Other demand-side	ρ_{10}	0.0003	(0.992)
Supply-side	ρ_{11}	-0.0063	(-3.022)
	Adj. R^2	0.697	
	D.W.	2.430	

Note: The dependent variable in Table 4 is the revision from the first to the second Quarterly Estimates of real GDP growth. The observation period is 2004Q4 to 2012Q3. *t*-values are in parentheses. The five rows below "From the source data for the first QE" show the estimated parameters and their *t*-values for the five principal components extracted from the source data both for the first and the second QEs. The three rows below "From the source data added for the second QE" show the estimated parameters and their *t*-values for the three principal components from the source data for the second QE.

Table 5: Root Mean Squared Errors for the Second QE

	Our approach	Professional forecasters
One week before the release date	0.12	0.19

Note: The column "Professional forecasters" shows the RMSE of the average of the nowcasts of the second QE by roughly ten professional forecasters. Their nowcasts are available about one week before the release of the second QE. The observation period for the RMSEs in this table is from 2004Q4 to 2012Q4.

Sources: Bloomberg, Nikkei.

Figure 1: Real-time Data of Real GDP Growth

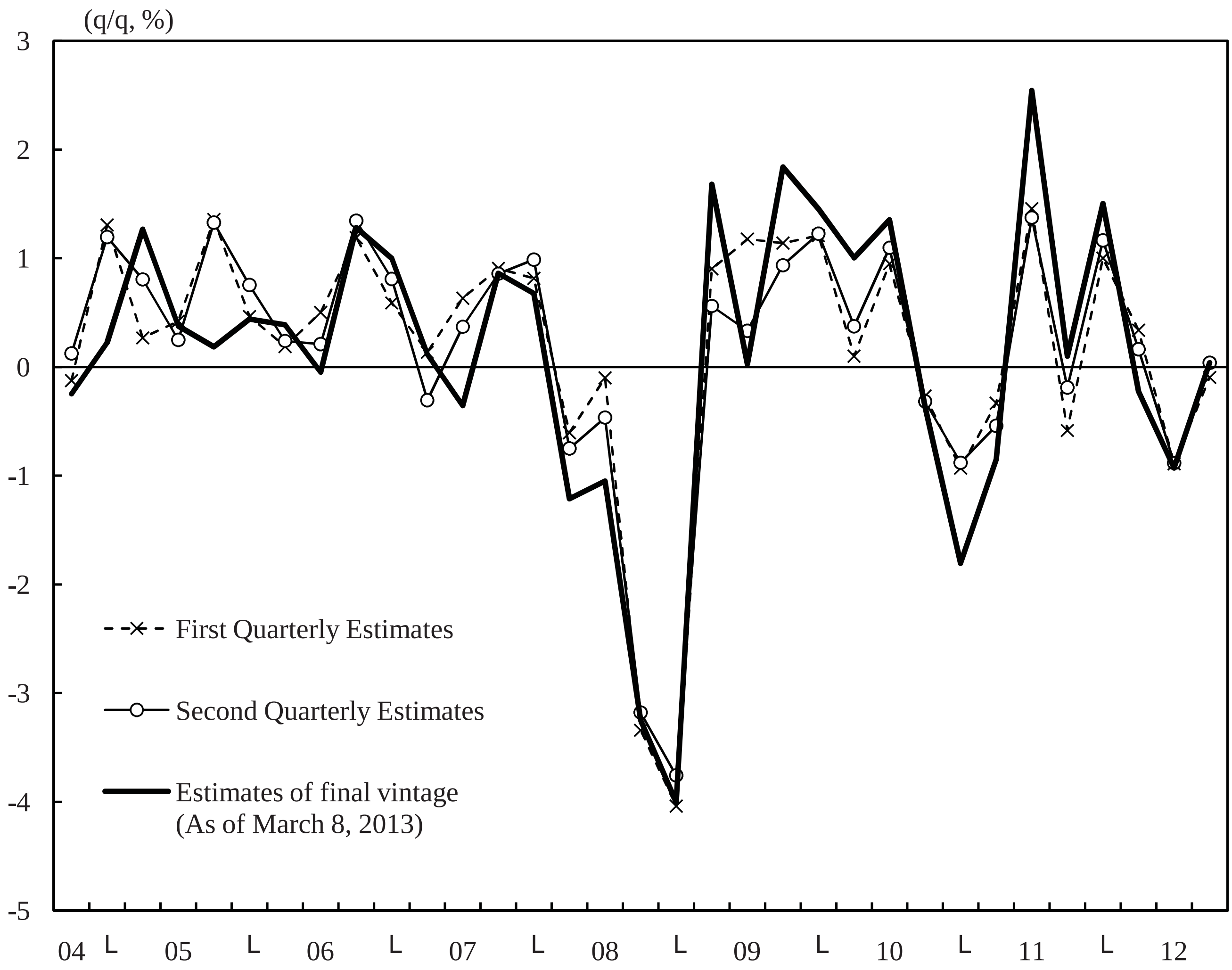


Figure 2: Official First QE and Model Estimates

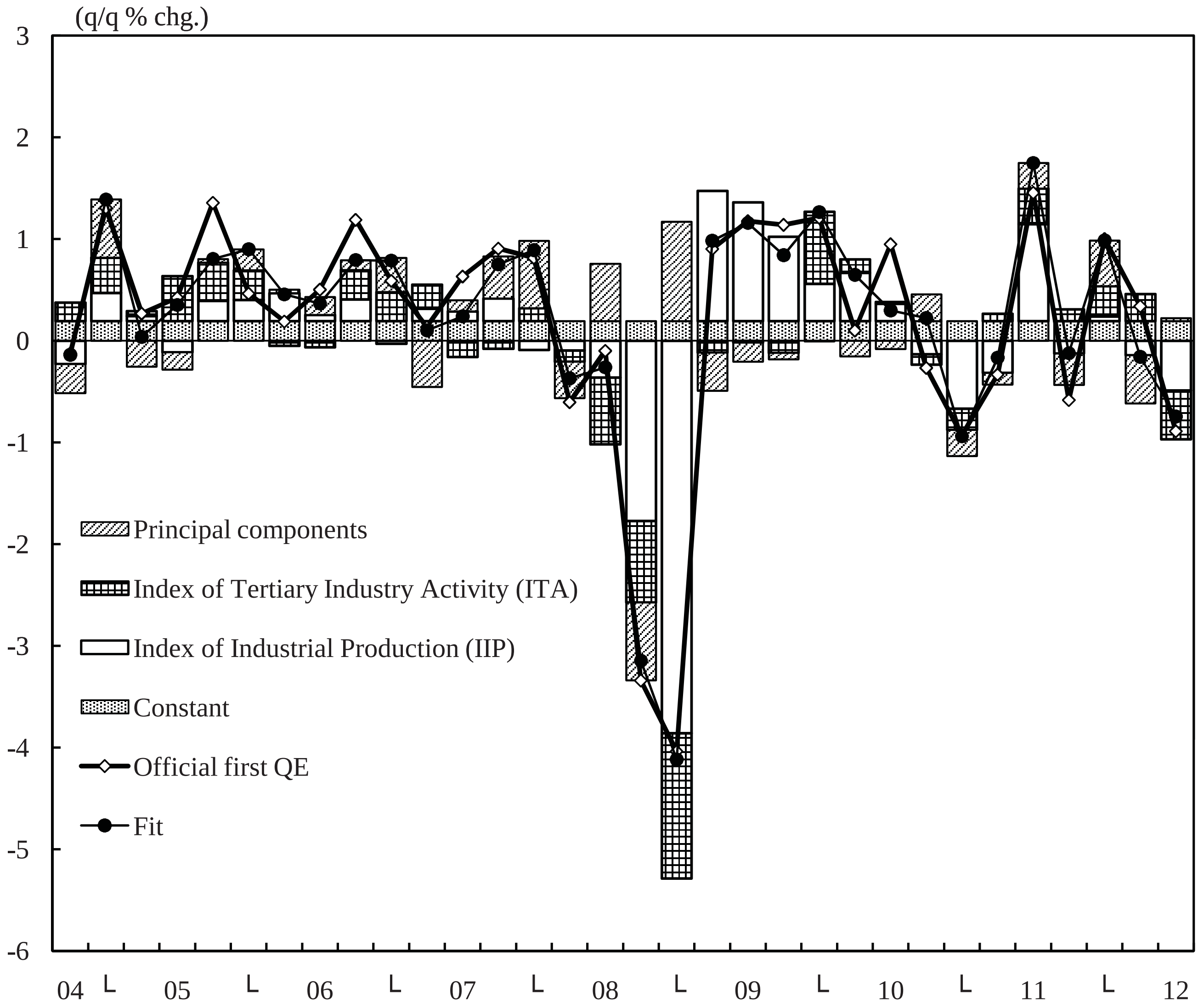


Figure 3: Estimates of Monthly GDP Growth

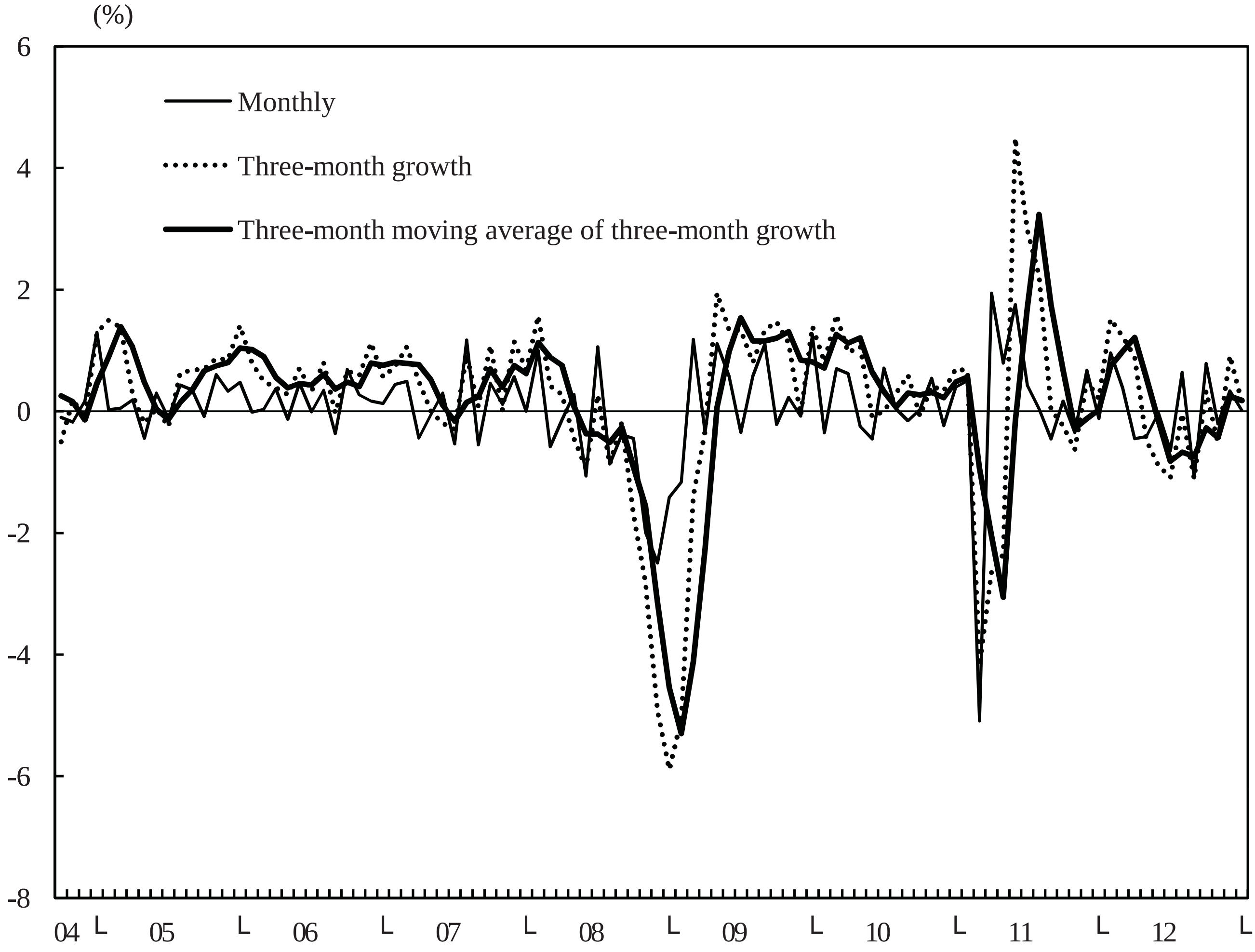
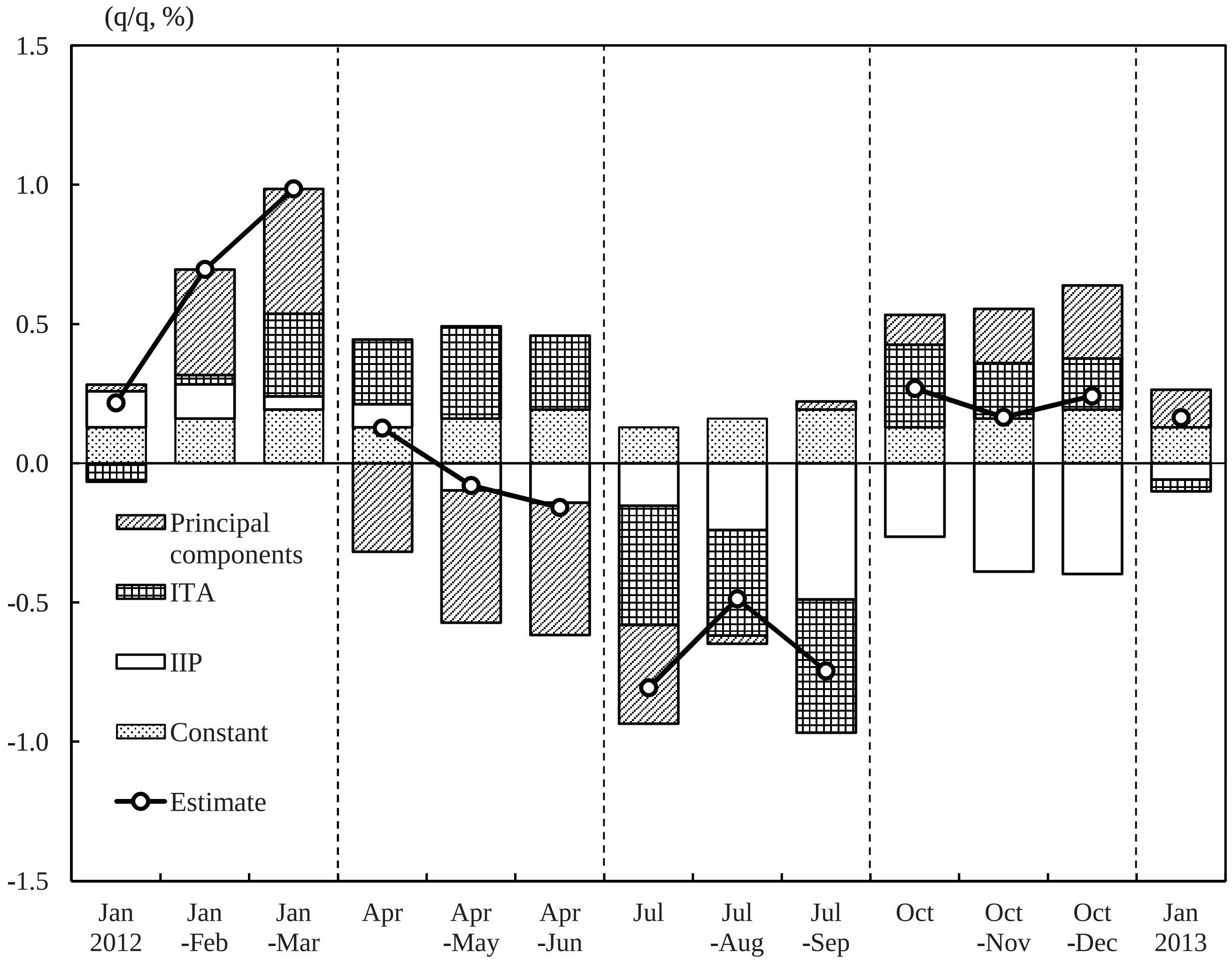


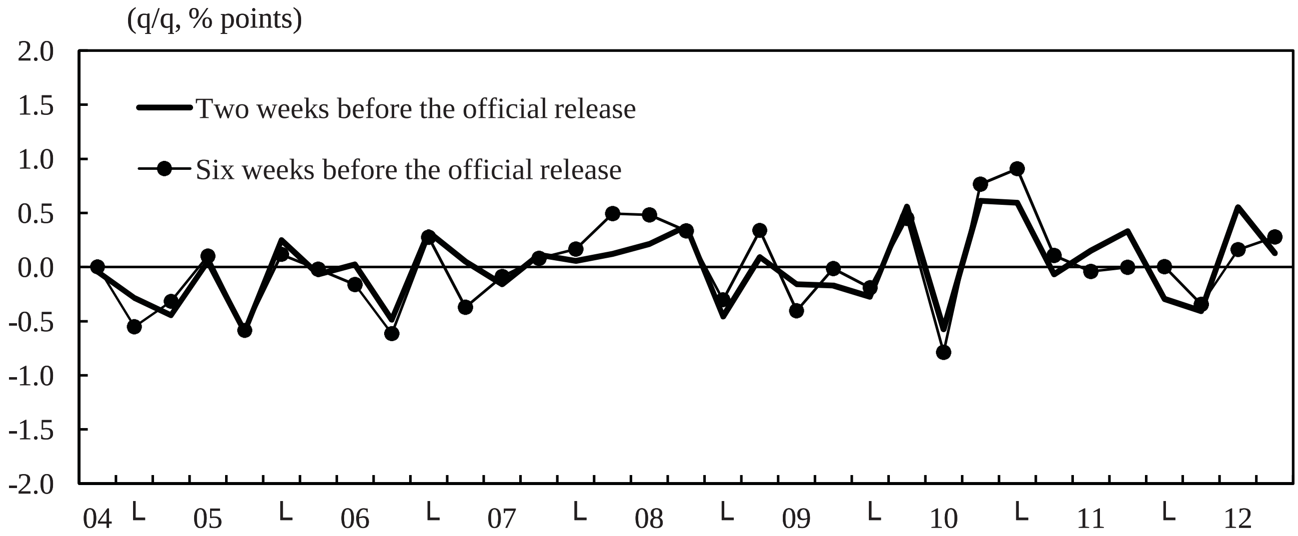
Figure 4: Monthly Estimates of Quarterly GDP Growth for Every Month



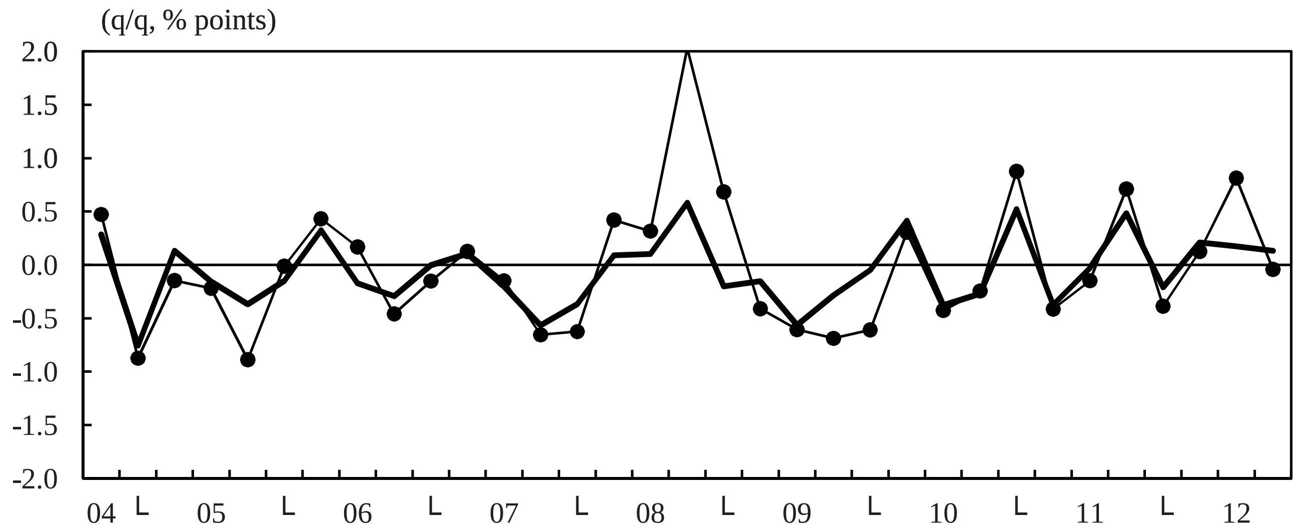
Note: The estimate in the first month within a particular quarter is the quarterly growth rate if the level of monthly GDP registered in the first month remained unchanged over the next two months. The second-month estimate is the quarterly growth rate if the level of monthly GDP in the third month was equivalent to the average of the first two months. The third-month estimate is equal to the estimate for the quarter.

Figure 5: Forecast Errors of the First QE

(a) Our approach

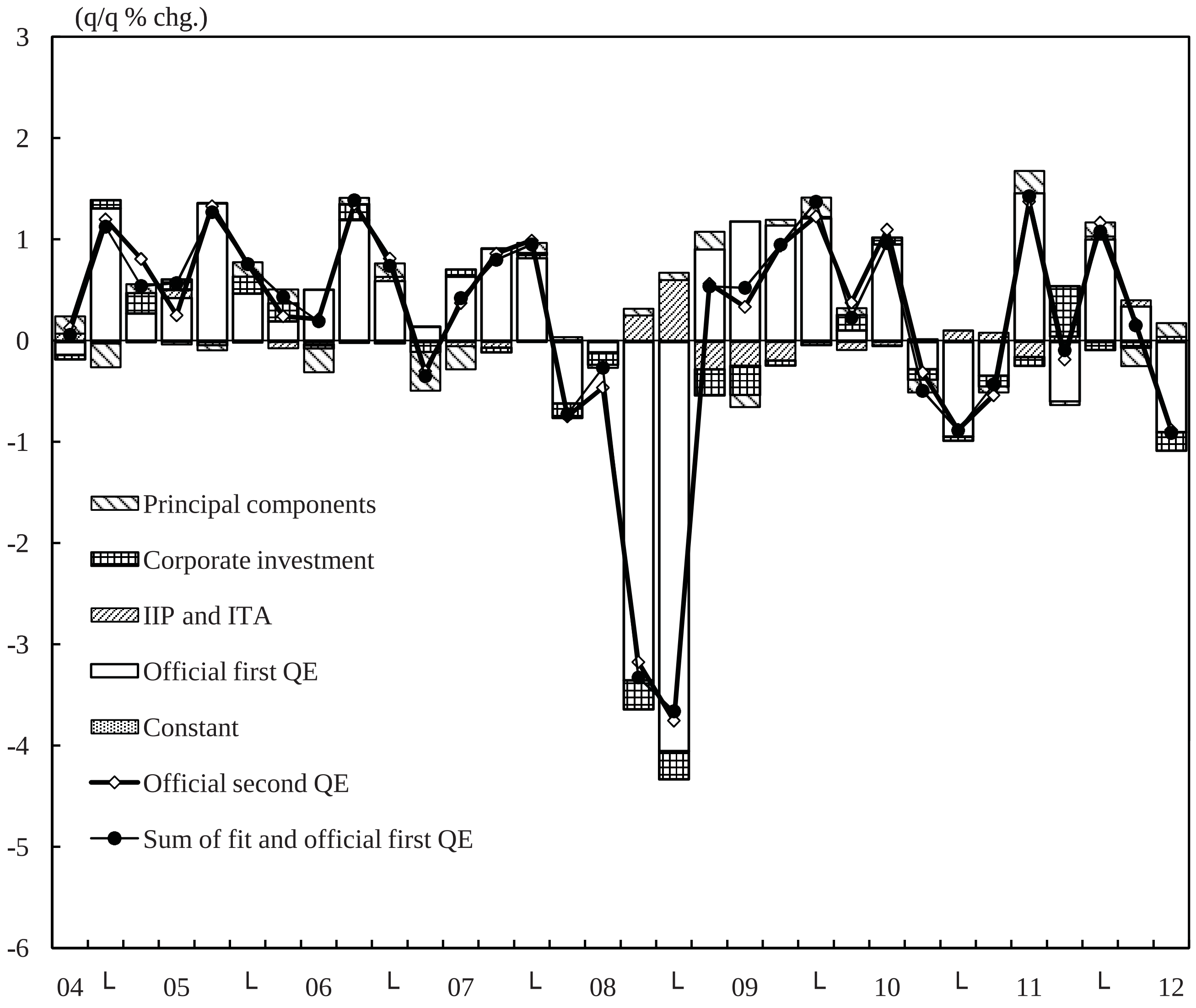


(b) ESP Forecast



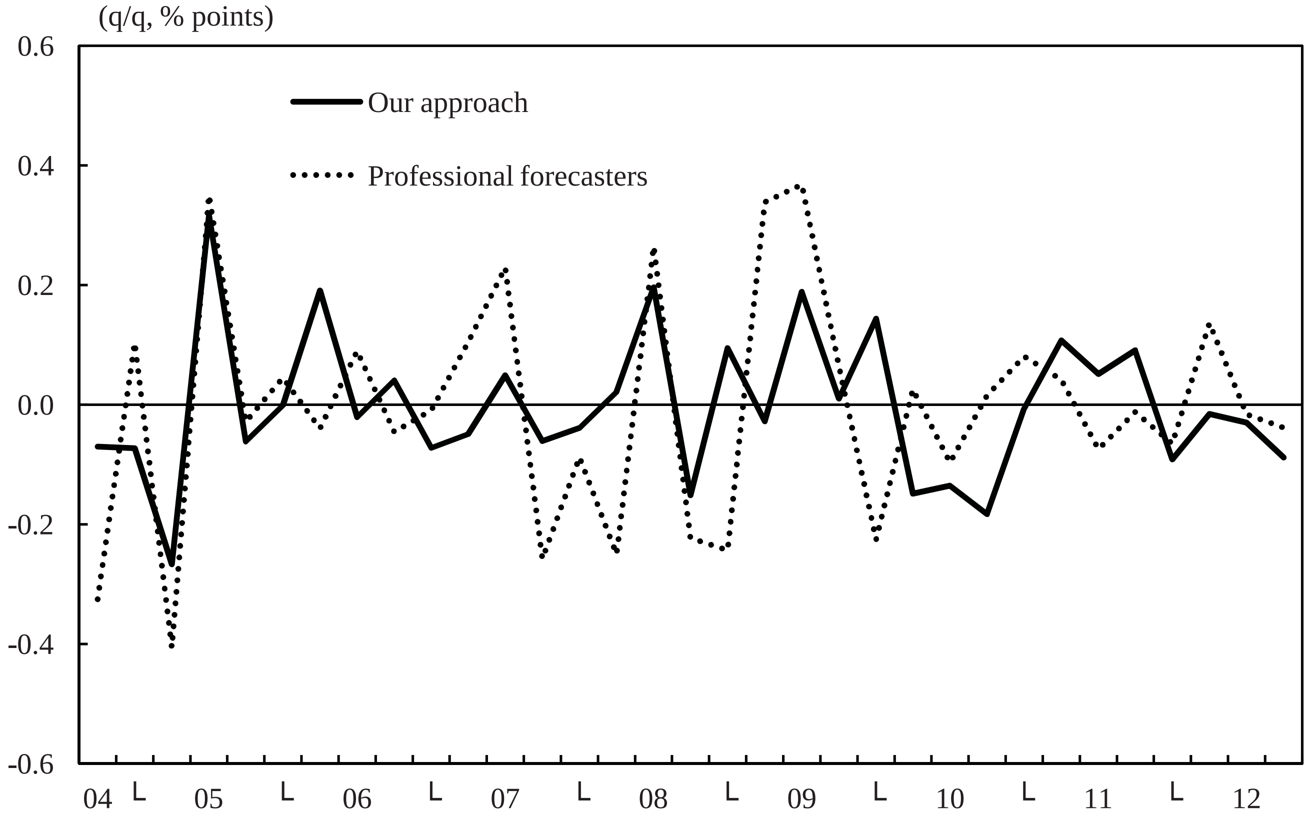
Source: ESP Forecast, Japan Center for Economic Research.

Figure 6: Official Second QE and Model Estimates



Note: The fit in Figure 6 equals the model estimates of revisions from the first to the second QE of GDP growth rates.

Figure 7: Forecast Errors of the Second QE



Note: See the note for Table 5 for details on the nowcasts by the professional forecasters.