Bank of Japan Working Paper Series

Constructing GDP Nowcasting Models Using Alternative Data

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No.22-E-9
July 2022

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July 2022

Abstract

With coronavirus (COVID-19) having a significant impact on economic activity, the existing GDP nowcasting model, using only monthly and quarterly economic data, has become difficult to forecast with high accuracy. In this paper, we attempt to improve the accuracy of GDP nowcasting models by using alternative data that are available more promptly. Specifically, we construct nowcasting models that incorporate sparse estimation by Elastic Net using weekly retail sales data and hundreds of daily Internet search volume data, in addition to conventional monthly economic data. For the model formulation and data selection, we prepare a large number of candidate models using the method of forecast combination, which combines multiple forecasting models, and select "Best models" which minimize the forecast error, including data after the spread of COVID-19. The analysis shows that the use of alternative data significantly improves the forecasting accuracy of the model, especially at the 2-month prior to release of GDP, when the availability of monthly and quarterly economic data are limited.

JEL classification: C52, C53, C55
Key words: Nowcasting, Alternative Data, Elastic Net, Forecast Combination.

[*] The author is grateful to Haruhiko Inatsugu, Seisaku Kameda, Takuji Kawamoto, Yoshiyuki Kurachi, Tomoaki Mikami, Teppei Nagano, Jouchi Nakajima, Kenichi Sakura, Hiroaki Yamagata, and colleagues at the Bank of Japan for comments and discussions. All remaining errors are the sole responsibility of the author. The views expressed in this paper are those of the author and do not necessarily reflect those of the Bank of Japan.
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1. Introduction

With the changing COVID-19 situation having a significant impact on economic activities, it is becoming increasingly important to understand accurately the most current economic situation in real time. In particular, GDP, which is a comprehensive indicator of a country's economic activities, is an important benchmark for economic policy management—but there is always a lag before its release. In Japan, it takes about one and a half months for the first preliminary estimates of GDP to be released. The attempt to forecast the current GDP in real time using the most up-to-date information is called "GDP nowcasting," and it has been attracting increasing attention worldwide in recent years.

GDP nowcasting efforts have been based on the concept of forecasting GDP using monthly and quarterly economic indicators that are released earlier than GDP. For instance, in the U.S., several Federal Reserve Banks have proposed nowcasting models based on this approach. Specifically, the Federal Reserve Bank of Atlanta and the Federal Reserve Bank of New York operate nowcasting models called "GDP Now" and "Nowcasting Report," respectively. They update their forecasts and post them on their websites[1]. In Japan, Hara and Yamane (2013), Bragoli (2017), Chikamatsu et al. (2018, 2021), Hayashi and Tachi (2022), and Urasawa (2021) propose nowcasting models based on these methods.

However, the performance of the existing nowcasting models, which only use monthly and quarterly indicators, has been deteriorating since the spread of COVID-19 in 2020[2]. This is partly due to the repeated introduction and then lifting of public health measures, which has increased the amplitude of economic fluctuations. The existing models which use traditional monthly and quarterly economic data with a (albeit relatively short) lag before publication, means the most up to date situation is not fully incorporated into the forecast values.

To overcome this problem, there have been many recent attempts to construct nowcasting models in each country that capture economic fluctuations earlier by introducing "alternative data" that are available at high frequency, such as daily or weekly[3]. For example,

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[1] GDP Now uses a Bridge model incorporating a factor model and a Bayesian VAR to make forecasts (Higgins, 2014). The Nowcasting Report, on the other hand, uses a state-space model to make forecasts (Bok et al., 2018).

[2] Urasawa (2021) shows that in nowcasting for Japanese GDP, the models' forecasting accuracy deteriorates markedly when the period since 2020 is included in the sample period. It notes that after the spread of the COVID-19 infection in 2020, it has become difficult to capture large fluctuations in economic change in real time using only traditional economic data.

[3] As defined by Kameda (2022), alternative data here is a generic term for data other than traditional economic data such as monthly and quarterly macroeconomic indicators and earnings disclosure data of listed companies.

Jardet and Meunier (2020) incorporate daily and weekly data such as the Baltic Dry Index and gasoline consumption in the U.S. into their Global GDP nowcasting model. They find that the constructing model outperforms models using only traditional monthly and quarterly economic data in the forecasting accuracy. Woloszko (2020) also constructs a GDP nowcasting model for 46 countries using daily available Internet search volume data. In contrast, for Japan, only a few studies examine the forecasting accuracy of nowcasting models after 2020, when COVID-19 began to spread[4]. Moreover, to the best of the author's knowledge, thus far, there are no previous studies on GDP nowcasting focusing on Japan that incorporate alternative data into the model.

Given this situation, this paper proposes a method of nowcasting Japanese GDP using alternative data and constructs best nowcasting models that include data for 2020 onward. Specifically, the following analysis takes as a starting point an existing GDP nowcasting model based on Chikamatsu et al. (2018), which the Research and Statistics Department of the Bank of Japan has utilized to grasp economic conditions. This model is a standard model for forecasting GDP from monthly and quarterly indicators. We refer to it as the "Benchmark model" in the sense that it serves as a benchmark for evaluating the forecasting accuracy of the new model constructed in this paper. The Benchmark model is a forecast combination model, which is obtained by simply averaging the following three forecasts: (i) estimates from the Bridge model; (ii) estimates from the CMIDAS (Combined Mixed-Data Sampling) model; and (iii) economists' GDP forecasts (in JCER ESP forecast survey) [5].

The new models we construct in this paper improve on the Benchmark model in the following two ways. First, we use alternative data as part of the estimation of the Bridge model. Specifically, we use (a) the Google Trends category search volume index, which is based on Internet search count data, and (b) the METIPOS retail sales index, which is POS (Point-Of-Sales) data from retail stores. Both data have the advantage of being published more quickly than conventional indices, with a lag of one to nine days before publication, and thus have the potential to capture GDP movements at an early stage. Second, we search for the combination of models with the highest forecasting accuracy, including data up to the recent period. In general, the number of candidate models grows astronomically as we must choose which economic data to use for estimation, which regression model to use, and how to combine these models to create a forecast combination. In this paper, we narrow down the candidate explanatory variables to seven based on previous research, and then examine

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[4] In the studies mentioned above, Hayashi and Tachi (2022) and Urasawa (2021) evaluate the forecast values of nowcasting models that include data beyond 2020.

[5] The Benchmark model adds real imports and exports to the explanatory variables, which are not used in Chikamatsu et al. (2018).

approximately 260,000 combinations of models that use these variables, then find the "Best models" with the smallest forecast error amongst them. To evaluate these models including the term with rapid economic fluctuations under the spread of COVID-19, we set the end of test sample period for the first quarter of 2021.

The rest of the paper is organized as follows. Section 2 introduces the Benchmark model on which the analysis in this paper is based, and then analyzes the evolution of its forecast accuracy before and after the spread of COVID-19. Section 3 describes the nowcasting method using internet search data and POS data. In Section 4, we search for the model with the highest forecast accuracy by trying all candidate forecast combination models. Section 5 evaluates the forecasting results of the Best models selected in Section 4, with comparisons to the Benchmark model. Section 6 concludes.

2. The Benchmark model

2-1. Overview

In this section, we present the Benchmark model that partially improves on the GDP nowcasting model by Chikamatsu et al. (2018). As mentioned above, the forecast values of this model are a simple average of the predictions from two econometric models (Bridge model and CMIDAS model) and economists' forecasts. In the two econometric models, we use monthly data as the explanatory variables, in order to forecast quarterly GDP as an explained variable.

2-1-1. Bridge model

The Bridge model is one of the leading methods for forecasting quarterly data from monthly data (see, e.g., Baffigi et al., 2004). In this model, the explanatory monthly data are converted to quarterly data in order to match the frequency of the explanatory and explained variables. Specifically, we estimate equation (1) using the OLS (Ordinary Least Squares) method.

$$y_t = \alpha + \sum_{i=1}^{N} \beta_i x_{i,t}^{Q} + \epsilon_t \tag{1}$$

where y_t is the quarterly real GDP growth rate and $x_{i,t}^{Q}$ is the quarterly equivalent of the monthly data of each explanatory variable $(i = 1, \ldots, N)$. Most of the indicators used as explanatory variables here are month-over-month growth rates (mom change), in which case the quarterly conversion method for $x_{i,t}^{Q}$ is based on Mariano and Murasawa (2003) and is calculated using equation (2) below[6].

$$x_{i,t}^{Q} = \frac{1}{3}(x_{i,3t}^{M} + 2x_{i,3t-1}^{M} + 3x_{i,3t-2}^{M} + 2x_{i,3t-3}^{M} + x_{i,3t-4}^{M}) \tag{2}$$

where $x_{i,3t-h}^{M}$ is the mom change h months ago from the last month of the quarter being forecast.

The explanatory variables in the Bridge model here ($x_{i,t}^{Q}$ in equation (1)) are (i) the index of tertiary industry activity (ITA, mom change); (ii) real exports (mom change); (iii) real imports (mom change); and (iv) Reuters *Tankan* index (first principal component of subcomponents)[7]. However, it is not always the case that all the monthly data in equation (2) are available at the time of the forecast. Therefore, in the Bridge model, we extrapolate the unavailable monthly data by using other economic variables that are already published. This extrapolation is an important characteristic of the Bridge model because accuracy of a single variable extrapolation affects the accuracy of the entire model[8].

For example, if ITA (ita_t, mom change) for month *t* is not available, the Benchmark model uses extrapolated value by linear regression equation (3). Its explanatory variables are published before the release of ITA data. Specifically, we use three explanatory variables: industrial production index (IIP_t, mom change), the Economy Watchers Survey DI for current conditions ($watcher_t$, household activity-related DI) and real sales value of wholesale industry (csc_t, mom change). We use the fitted value of the equation as extrapolated value of ITA ($\widehat{ita}_t$).

$$\widehat{ita}_t = \alpha + \beta_1 IIP_t + \beta_2 watcher_t + \beta_3 csc_t \tag{3}$$

Then, we calculate quarterly data by combining the monthly actual values and the extrapolated values and used them as explanatory variables in the Bridge model.

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6 When using the level of an indicator as an explanatory variable, we use the simple average of monthly data during the quarter.

7 Reuters *Tankan* index (first principal component of subcomponents) is defined as the first principal component extracted from 18 Reuters *Tankan* series by industry, using sparse principal component analysis in Zou et al. (2006).

8 In addition to extrapolating unpublished monthly data with another indicator, there are other methods of extrapolation based on the assumption that the variables follow some structural time series models like ARIMA model (see, e.g., Bańbura et al., 2013). While this method does not require a priori assumption of a relationship with another indicator, the accuracy of extrapolation is likely to deteriorate when the pattern of data fluctuation changes significantly compared to the past, as in the case of economic fluctuations during the spread of COVID-19.

2-1-2. CMIDAS model

Along with the Bridge model, the mixed-data sampling (MIDAS) model is another leading nowcasting method for forecasting quarterly GDP from monthly data (see Foroni and Marcellino, 2014; Kuzin et al., 2013). In the case of GDP nowcasting using the MIDAS model, the monthly data are used as explanatory variables to predict the real GDP growth rate for the quarter, as in equation (4) below[9].

$$y_t = \alpha + \sum_{i=1}^{N} \sum_{j=0}^{l_i} \beta_{i,j} x_{i,3t-j}^{M} + \epsilon_t \tag{4}$$

Unlike the Bridge model, extrapolation is not needed as the right-hand side of (4) consists only of published monthly data. On the other hand, every time the new data of explanatory variables is published, the number of explanatory variables changes. Therefore, it has been pointed out that the forecast values are likely to change significantly each time they are updated if the MIDAS model alone is used. To avoid such unstableness, previous literature proposes forecast combination, which combines multiple MIDAS models (see, e.g., Andreou et al., 2013; Anesti et al., 2017). Such models are called Combined MIDAS (CMIDAS) models and also used in the Benchmark model.

The CMIDAS model in the Benchmark model uses four explanatory variables: (i) ITA (mom change); (ii) the index of industrial production (IIP, mom change); (iii) real sales value of wholesale industry (mom change); and (iv) Reuters *Tankan* index (first principal component of subcomponents). A total of 14 MIDAS models are estimated separately based on combinations of these four variables, and the forecast values based on each MIDAS model are calculated[10]. These 14 forecasts are then averaged to produce the CMIDAS model predictions.

2-1-3. Forecast combination

In the field of time series forecasting, many previous studies point out that combining the forecasts of multiple different models is likely to improve forecast accuracy than using a single model (see, e.g., Winkler, 1989; Timmermann, 2006). Reasons for this include: (i)

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[9] There are two ways to estimate a MIDAS model: one is to assume a specific structure like the Almon lag model among the coefficients of lag variable. The other is to regress the coefficients using OLS without assuming any particular relationship among the coefficients (Unrestricted MIDAS). The latter method is used in the Benchmark model, and is also followed in the new model described in this paper.

[10] The Benchmark model places upper limits on the number of parameters to be estimated, thus the MIDAS model with all of the above four variables as explanatory variables is not used.

multiple models are more likely to capture structural changes of generating the data to be forecast (Diebold and Pauly, 1987); and (ii) it is easier to reduce the effects of formulation errors of the model (Stock and Watson, 2004).

Based on these studies, Chikamatsu et al. (2018) compare forecast errors for several forecast combination models for nowcasting Japanese GDP. They find that the combination model which is the average of forecasts by Bridge model, CMIDAS model, and the economists' GDP forecasts outperforms other models as a whole. The Benchmark model in this study also uses same forecast combination patterns[11]. However, Chikamatsu et al. (2018), on which our Benchmark model is based, evaluate the forecasting accuracy only using the sample data through the first quarter of 2018. This means that the volatile developments in Japan's economy following the spread of COVID-19 are not considered in their evaluation. Therefore, the next section will review the evolution of the Benchmark model's forecasting accuracy up to the most recent period.

2-2. Changes of forecast accuracy in the Benchmark model

In this section, we review how the forecasting accuracy of the Benchmark model has varied over the most recent period. Although there are several indices to evaluate forecast accuracy, the Root Mean Squared Error (RMSE) of the out-of-sample forecast, which many previous studies use, is also used below.

In evaluating a nowcasting model, the number of months prior to GDP release date when the the forecast values are evaluated, is important. The point in time at which the accuracy of the forecast should be emphasized depends on the purpose of its use. In this paper, we calculate three forecasts at the following three points in time respectively: (i) the forecast value using the data set at the time immediately before the release of the first preliminary estimate of GDP (Forecast at release date); (ii) the forecast value at the time one month prior to the release; and (iii) the forecast value at the time two months prior to the release. Furthermore, to evaluate the average forecast accuracy through each forecast time point, we calculate the average of forecast error (RMSE) for the three time points (i)-(iii) as "integrated forecast error (integrated RMSE)"[12].

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[11] Chikamatsu et al. (2018) provide a comparison of economists' GDP forecasts with forecasts compiled by Bloomberg, and ESP Forecasts published by JCER. They consider both forecast averages from the survey, and the results show that the forecast combination model, which includes the latter, performs better. This paper also uses the ESP Forecasts as the economists' forecast values.

[12] As in previous studies such as Chikamatsu et al. (2018) and Angelini et al. (2011), we use latest vintages of GDP and explanatory variables, which means that they reflect all revisions made after the previous publication. Moreover, for indicators such as the METIPOS retail sales value index, which began

Chart 1 shows the RMSE of the Benchmark model forecasts when we calculate for the sample from the first quarter in 2013 to each subsequent time point. For comparison, the RMSE calculated from the economists' GDP forecasts are also included. For the period up to the first quarter in 2020, the integrated RMSE from the Benchmark model was stable at a lower level than that RMSE from the economists' forecasts. On the other hand, from the second quarter of 2020 onward, the forecast accuracy of both the Benchmark model and the economists' forecasts deteriorated significantly. Looking at the forecast errors of the Benchmark model at each forecast point in time, the forecast accuracy has deteriorated significantly since the second quarter in 2020 for the 2-month prior forecast. The forecasts at release date and 1-month prior forecast, while worsening somewhat, are still superior to the economists' forecasts.

In this regard, we check the RMSE for each of the three forecasts that make up the Benchmark model (Bridge model, CMIDAS model, and economists' forecasts) in Chart 2. We find that the RMSE for the CMIDAS model worsens significantly from the second quarter of 2020 onward in the 2-month prior forecast. As mentioned earlier, the CMIDAS model is a method of forecasting quarterly GDP using monthly data as explanatory variables. At the time of the 2-month prior to GDP released date, many of the explanatory variables are only available for the first month of the quarter, thus MIDAS model can use only the first month's data to forecast that quarter. Since 2020, the spread of COVID-19 and introduction of public health measures have resulted in large monthly fluctuations in economic indicators. Therefore, the CMIDAS model, which forecasts based only on the first month's data, has become unstable and its forecasting accuracy has declined significantly. Although not as bad as the CMIDAS model, the accuracy of the Bridge model's 2-month prior forecast has also been constantly poor, and it has pushed down the accuracy of the Benchmark model's forecast as a whole.

3. Improvement of nowcasting model using alternative data

As we identify in Section 2, the deterioration in the accuracy of the Benchmark model's forecasts since second quarter of 2020 has occurred mainly in the 2-month prior forecasts, where the available data set is limited. This is likely due to publication lag of traditional monthly economic data, and the use of more promptly available data can be a strategy to

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to be published regularly after the first quarter of 2013, we assume that the data are available prior to the periodical publication, with the same publication schedule as in the most recent period. Therefore, the data here is strictly different from a data set that is available at the time of each forecast point. In this sense, the analysis here is based on "pseudo-real time" data.

improve accuracy. Therefore, this paper attempts to use alternative data as part of the Bridge model's extrapolation equation.

Specifically, we rebuild Bridge model's extrapolation equations (3) (ITA extrapolation equation) in the Benchmark model[13]. We add the following two types of alternative data to the explanatory variables in equation (3)： (i) Google Trends category search volume index; and (ii) METIPOS retail sales value index. In this paper, we use alternative data only for ITA extrapolation. This is because it is published the latest (approximately 42-51 days after the last day of the coverage month) amongst all explanatory variables used in this paper, so it is highly dependent on extrapolation compared to other indicators. In addition, in the Benchmark model, ITA has the largest extrapolation error in its forecast for 2020 and beyond (Chart 3). Given these facts, a more accurate forecast of ITA would contribute to improve the accuracy of the GDP forecast.

3-1. Google Trends category search volume index

Google Trends is a data site that provides time series of the number of searches for particular keywords, such as "travel" or "restaurant" on the Google search engine. Some previous studies argue that search volume time series for particular keywords show a high correlation with movements in economic activity and are useful for forecasting various economic indicators, including GDP (see, e.g., Vosen and Schmidt, 2011; Matsumoto et al., 2013; Ferrara and Simoni, 2019; Woloszko, 2020). On the other hand, among the myriad of search words, it is difficult to identify which words are appropriate to use in the estimation of ITA. In this paper, instead of using the number of searches for individual words, we use "Category search volume index" data, another data acquisition method provided by Google Trends.

Category search volume index is data on the volume of searches for terms related to a certain topic (category), added together based on Google's algorithm. For example, the category of "hotels and accommodations" could include the number of searches for the words "hotels" and "accommodation," plus that for category-related search terms such as "Tokyo hotels" and "accommodations recommended". In total, there are 1,132 categories in Google Trends. However, in this paper, we only use the categories satisfying the following two conditions.

The first condition is that the categories are considered to be directly related to short-term economic fluctuations. Many of the 1,132 categories listed above are not considered to

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[13] The other explanatory variables in Bridge model are also extrapolated according to their respective extrapolation formulas, as well as ITA (see Appendix for details).

satisfy this condition, such as "astronomy" and "obesity." Therefore, out of the 1,132 categories, we select 252 categories that are considered a priori to be related to short-term economic fluctuations, such as categories related to the demand for specific goods and services (e.g., "wine" and "weddings") and categories that are considered to reflect broad business sentiment (e.g., "bankruptcy" and "retail trade").

As the second condition, we exclude search volume data whose values significantly depend on when the data is downloaded. According to Medeiros and Pires (2021), the data values of Google Trends is based on sampled data. Thus, if the number of searches for a given word or category is significantly scarce, the data can change significantly depending on the time point at which the data is downloaded. Since such a problem affects the reproducibility of the results, we eliminate these "volatile" series. Specifically, we take multiple samples of the same search count data at different times, and we use categories for which the standard deviation between the samples was less than a certain level[14]. The number of categories that satisfy both the first and second conditions is 217.

In the Google Trends data, there are some discontinuities due to changes such as that of definition. To deal with this, we adjust data with reference to Woloszko (2020)[15]. Seasonal adjustments are conducted to the adjusted series. We call them search volume index for each category in this paper. To eliminate their long-term trend, we use the deviation from the trend calculated by the Hodrick-Prescott filter[16].

Chart 4 illustrates three examples of search index. The search number for "Travel Guides and Travelogues" shows a significant drop after the start of 2020 due to the impact of the spread of COVID-19, reflecting a decline in demand for travel arising from such as public health measures. In addition, looking at changes in "Auto Financing," movements reflecting the front-loaded increase and subsequent decline in demand of automobiles prior to and after the consumption tax rate hikes in April 2014 and October 2019 are seen, suggesting a link with automobile sales. Trends in "Mail and Package Delivery" shows a large increase during the 2020 COVID-19 outbreak, possibly capturing an increase in so-called "stay-at-home demand."

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[14] Specifically, we take five samples at 10-minute intervals for each index, and use only the series whose standard deviation between those samples is less than 0.01.

[15] The geographic coverage changes implemented by Google in January 2011 and the system changes and improvements in January 2016 have created gaps in the data (Woloszko, 2020). These effects are eliminated by connecting the year-over-year growth rate for the month in which the gaps occurred as the same as that for the month right before the gaps occurred, and then extending the following month with the previous mom change before the gap adjustment.

[16] The smoothing parameter (λ) in the Hodrick-Prescott filter is set to 14,400.

3-2. METIPOS retail sales value index

METIPOS retail sales value index (METIPOS) is based on the POS data of approximately 10,000 retail stores. It is compiled by type of retail business and is published quickly. Particularly since the spread of COVID-19, such POS data have been used in various studies as a tool for real-time analysis of economic conditions (see, e.g., Konishi et al., 2021). However, to the author's knowledge, no studies have used such data for GDP nowcasting in our country. We convert weekly sales value indices to monthly and make seasonally adjusted mom change for the five types of retail businesses: (i) supermarkets; (ii) drug stores; (iii) convenience stores; (iv) home improvement stores; and (v) large electronics retail stores. We use these five series for the following estimation.

3-3. Estimation method

The total number of explanatory variables for the extrapolation of ITA in the Benchmark model together with the above alternative data exceeds 200. On the other hand, the sample period for the estimation is at most nine years, or about 100 months. Thus, the number of samples is less than the number of explanatory variables, making the OLS estimation impossible. In this paper, we avoid this problem by using the Elastic Net estimation, a machine learning technique, to estimate coefficients and select variables appropriately at the same time.

When estimating a regression equation, "sparsity" means the property that the appropriate variables are automatically selected, i.e., parameters other than the relevant variable are set to zero. Among the several estimation methods with sparsity, a typical method is the Lasso regression method proposed by Tibshirani (1996). However, Lasso regression cannot estimate regression equations if number of samples n is less than number p of explanatory variables, and large p leads to unstable estimates due to multicollinearity.

The Elastic Net method proposed by Zou and Hastie (2005) addresses these issues by being robust to multicollinearity while retaining sparsity[17]. It is also suitable for estimations with relatively short sample periods and a large number of explanatory variables, as in this

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[17] When a group of variables with multicollinearity is included in the explanatory variables, Lasso has a tendency for only one coefficient in the group to be non-zero, and the other coefficients in the group to be estimated as zero. Moreover, the values of the coefficients themselves may be fragile to slight change of sample data. On the other hand, in the similar situation, the coefficients estimated by Elastic Net has "group effect" property, which coefficients among groups have almost similar values (Zou and Hastie, 2005). The group effect is a desirable property because it makes regression coefficients stabilize, or not change significantly due to slight differences in the data, even when there is multicollinearity among variables.

paper, because it does not have the restrictions on the number of samples and explanatory variables that exist in Lasso regression.

In the Elastic Net estimation, the coefficients of the explanatory variables are estimated in equation (5):

$$\widehat{\boldsymbol{\beta}} = \underset{\boldsymbol{\beta}}{\boldsymbol{argmin}}\left(\frac{1}{2n}[\boldsymbol{Y}-\boldsymbol{X\beta}]^2 + \lambda\left[\alpha\sum_{j=1}^{p}|\beta_j| \ +\left(\frac{1-\alpha}{2}\right)\sum_{j=1}^{p}\beta_j^2\right]\right) \tag{5}$$

where $\boldsymbol{Y}$ is a vector of explained variable, $\boldsymbol{X}$ is a matrix of p explanatory variables, $\boldsymbol{\beta} = (\beta_1, \dots, \beta_p)'$ is a vector of coefficients, λ and α are regularization parameters ($0 < \lambda$, $0 < \alpha < 1$), and n is the number of samples. The first term in parentheses on the right side is the sum of error squares of the regression equation, which is the same statistic used in OLS. The second and third terms are called regularization terms, which are specific to the Elastic Net method. These terms become larger as the coefficients become away from zero, and they work like penalties imposed in the minimization problem. For this reason, it is also called a penalized regression model.

The new ITA extrapolation equation is estimated by the Elastic Net method using the following equation (6).

$$ita_t = c + \sum_{i=1}^{217}\beta_i^{gt}gt_{i,t} + \sum_{j=1}^{5}\beta_j^{mp}mp_{j,t} + \sum_{k=1}^{4}\beta_k^{x}x_{k,t} + \epsilon_t \tag{6}$$

where ita_t is ITA (mom change), $gt_{i,t}$ is the search volume index for category *i* in Google Trends (mom difference in deviation rate from trend), $mp_{j,t}$ is the METIPOS of retail business type j (mom change). $x_{k,t}$ are three traditional data already used in the Benchmark model: (i) IIP (mom change); (ii) Economy Watchers Survey DI; and (iii) real sales values of wholesale industry (mom change). Moreover, we add (iv) the number of new passenger car registrations (mom change) as a new explanatory variable. Although the number of new passenger car registrations is not considered in the Benchmark model, we add it because it has been used in previous studies that have conducted GDP nowcasting for Japan, such as Bragoli (2017) and Hayashi and Tachi (2022). Finally, we use 226 indices as explanatory variables. All explanatory variables are standardized so that the mean is set to 0 and the variance is set to 1.

For actual estimation, it is necessary to set the regularization parameters (λ, α) in equation (5). In this paper, the parameters are set by grid search method. That is, we prepare multiple candidate parameters, and search for the parameter combination that minimizes the out-of-sample forecast error for the ITA from January 2014 to March 2021[18].

3-4. Estimation result

Chart 5 shows the estimation results for the ITA extrapolation equation, with the longest sample period (from November 2012 to March 2021)[19]. Among 226 explanatory variables, there are 141 variables excluded by sparse estimation (with zero coefficients), and 85 variables with non-zero coefficients.

The variables with the largest regression parameters, i.e., the variables with the largest average contribution to the forecast values, are the traditional data series such as real sales values of wholesale industry, new passenger car registrations, and IIP, followed by the METIPOS. Looking at Google Trends with relatively large coefficients, it includes indicators that indirectly capture trends in travel services and automobile sales, such as "Travel Guides and Travelogues" and "Auto Financing." On the other hand, there are also variables with negative sign. Looking at those with large absolute coefficients, there are search volume indices such as "Online Video" and "Mail and Package Delivery". These categories see a large increase amid the so-called "stay-at-home demand" under the spread of COVID-19, and are negatively correlated with ITA, which has fallen sharply in level since 2020.

Based on this estimation equation, we calculate out-of-sample forecast values for ITA (forecast values using data available immediately before ITA publication) since 2015 in Chart 6. The chart shows that the out-of-sample forecasts from the Elastic Net estimation have a significantly lower RMSE than that used in the Benchmark model, which means forecast accuracy has improved. In particular, the Elastic Net estimation accurately predicts the movements that occurred in September-October 2019 due to the front-loaded increase and subsequent decline in demand prior to and after consumption tax rate hike, as well as the rapid economic fluctuations under the spread of COVID-19 from March 2020 onward. This implies that Elastic Net forecasts accurately predict actual values when the economic fluctuations become volatile. We also see that the contribution of alternative data (Google Trends and METIPOS) to the forecasted values of ITA by Elastic Net estimation is

[18] Specifically, both λ and α are selected between 0.1 and 0.9 in increments of 0.1, and the parameter combination with the smallest forecast error is selected by trying all combinations. The parameters here selected are $\lambda = 0.1$ and $\alpha = 0.2$.

[19] Due to the sample size limitation of the METIPOS, we use the Elastic Net extrapolation of the ITA from the first quarter of 2014. Prior to that, Google Trends and the METIPOS are removed from the explanatory variables in equation (6) and the equation estimated by OLS method.

reasonably large.

As described above, the results show that the forecasting accuracy of ITA can be greatly improved by utilizing alternative data[20]. In the next section, we examine the model with the highest forecast accuracy while using the Bridge model incorporating this new extrapolation formula.

4. Selecting Best models

In this section, while retaining the basic model framework of Bridge and CMIDAS used in the Benchmark model, we examine which forecast combination can maximize the accuracy of the GDP forecast up to the most recent period by comparing forecast errors of all candidate combinations.

4-1. The procedure of selecting Best models

In constructing the new nowcasting model, candidates for the explanatory variables are basically the same as the Benchmark model. From the variables used in the Benchmark model, six indicators continue to be used in this paper: (i) ITA; (ii) IIP; (iii) real exports; (iv) real imports; (v) Economy Watchers Survey DI; and (vi) real sales values of wholesale industry[21]. As mentioned in Section 3, we also add (vii) the number of new passenger car registrations, which is frequently used in previous studies for Japanese GDP nowcasting. Thus, we create candidate models from seven indicator combinations.

In building the Benchmark model, the forecast combination, which uses the Bridge model, the CMIDAS model, and economists' forecasts, is considered. In addition, we newly introduce a Combined-Bridge (CBridge) model. Like the CMIDAS model, CBridge model attempts to construct a highly robust model against formulation errors and structural changes

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[20] In the Elastic net extrapolation equation, the coefficients are re-estimated at each data update. Therefore, the value of the coefficients changes over time, reflecting the correlation between each series and ITA at any given time. We confirm that the forecasting accuracy deteriorates when we fix the coefficients at a certain point in time instead of updating them.

[21] We do not use Reuters *Tankan* index (first principal component of subcomponents) as candidate of explanatory variables, though it is used in Chikamatsu et al. (2018) and the Benchmark model. This is because of the following two reasons. First, we find the contribution of that index to forecast error was smaller relative to other explanatory variables, when we extended the estimation period to the first quarter of 2021. Second, the calculation of the first principal component uses sparse estimation and is computationally burdensome due to optimization of hyperparameters and other factors. As in this paper, when trying out several hundred thousand specifications, including the Reuters *Tankan* would significantly increase the estimation load.

by using a simple average of the forecast values of multiple Bridge models[22].

We use the following steps to build the new nowcasting models (Chart 7).

(i) Bridge model estimation

We make total of 127 ($2^7 - 1$) sets of explanatory variables combining the above seven indicators and estimate Bridge model for each of the 127 explanatory variables sets. Then, we calculate three types of forecast values (forecasts at release date, 1-month prior forecasts, and 2-month prior forecasts) and forecast error (RMSE) of GDP for each forecast value. The simple average of those forecast errors (integrated RMSE) is then calculated and select the top 10 models with the smallest integrated RMSE of the 127 models.

(ii) CBridge model estimation

We create a set of 1,023 ($2^{10} - 1$) combinations from the 10 Bridge models selected in (i) and calculate average forecasts for each CBridge model set.

(iii) CMIDAS model estimation

We estimate CMIDAS models for the 127 sets of explanatory variables created in (i) above. Specifically, we estimate MIDAS models for all possible combinations of each set of variables, and the forecasts of the CMIDAS model are calculated by simply averaging the forecasts of those MIDAS models[23].

(iv) Making forecast combination

Next we make forecast combination of three forecasts value (a) ~ (c): (a) one forecasts from the CBridge model estimated in (ii) (1,023 patterns); (b) one forecasts from the CMIDAS model estimated in (iii) (127 patterns); and (c) economists' forecast (only 1 pattern).The total number of combinations above is 129,921 (1,023 x 127 x 1). In addition, we also add the average only of the CBridge model forecast and the economists' forecast, and the average of the CMIDAS model forecast and the economists' forecast to the

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[22] Though there are several weighting methods for combining forecasts through forecast combination, we use simple average in this paper. This is based on the rule of thumb that the simple average of forecasts generally performs better than that using complex weighting methods, or so-called "Forecast Combination Puzzle" (Stock and Watson, 2004; Smith and Wallis, 2009). Chikamatsu et al. (2018) also examine multiple weighting methods, but finally conclude that the forecast combination model using simple average has the best forecasting accuracy.

[23] For example, when estimating a CMIDAS model for the set of explanatory variables "ITA, IIP, and real exports," we first estimate seven MIDAS models respectively: (i) using only ITA as explanatory variable; (ii) IIP only; (iii) real exports only; (iv) ITA and IIP; (v) ITA and real exports; (vi) IIP and real exports; and (vii) ITA, IIP, and real exports. Then we simply average the forecast of these seven MIDAS models, and call them the forecasts of CMIDAS model.

candidates. As a result, there are 131,071 candidate forecasts. We calculate integrated RMSE of all candidates and select the forecast combination model with smallest integrated RMSE among them as the "Best model".

The above procedure complies with the Benchmark model and uses economist forecasts (JCER ESP Forecasts) as part of the model. On the other hand, if one considers the advantage of the nowcasting model is calculating forecast values mechanically, or without arbitrariness, one could rather think that it is undesirable to use economist forecast values in the model. In light of this view, we also consider another procedure for making forecast combinations, in which the process in (iv) above is changed to (iv') below.

(iv') Making forecast combination (excluding ESP)

We make forecast combination of two forecasts value (a) and (b): (a) one forecasts from the CBridge model estimated in (ii) (1,023 patterns); (b) one forecasts from the CMIDAS model estimated in (iii) (127 patterns). The total number of combinations above is 129,921 (1,023 x 127). In addition, we also add the CBridge model forecast and the CMIDAS model forecast themselves to the candidates. As a result, there are 131,071 candidate forecasts. We calculate integrated RMSE of all candidates and select the forecast combination model with smallest integrated RMSE among them as the "Best model excluding ESP".

4-2. The result of Best models' selection

Based on the procedures in the previous section, Charts 8 and 9 list the models with small integrated RMSE for each stage of the selection procedure.

Looking at the best 10 models with the smallest integrated RMSE in the estimation of the Bridge model in step (i), all of them use ITA that introduced the framework of extrapolation estimation using alternative data, as explanatory variables (Chart 8(2)). Already at this stage, the integrated RMSE of the top 10 models are below that of the Benchmark model, largely due to the lower RMSE in the 2-month prior forecast. Similarly, the CBridge model in step (ii), which is calculated by combining these 10 Bridge models, also improves its forecasting accuracy, especially for the 2-month prior forecast (Chart 8(3)). On the other hand, looking at the top 10 CMIDAS models in step (iii), the integrated RMSE deteriorates compared to the CBridge model and the forecast error is larger even compared to the Benchmark model (Chart 9(1)). As discussed in Section 2, the worsening of forecasts in the Benchmark model is more pronounced in the CMIDAS models, and we confirm that this trend is almost unchanged in other combinations of explanatory variables.

As a result of step (iv), the "Best model" with the smallest integrated RMSE is a model that combines the economists' forecasts and the Bridge model, whose explanatory variables are ITA, real exports, real imports, the Economy Watchers Survey DI, and new passenger car registrations (Chart 9(2) and Chart 10). The "Best model excluding ESP" is a CBridge model combining five Bridge models (Chart 9(3) and Chart 10). In all of the Bridge model equations that make up the forecast combination, ITA with the extrapolation using alternative data are employed as explanatory variables. It is interesting that both Best models do not employ CMIDAS models, which are different from the Benchmark model.

5. Performance of Best models

In this section, we check the forecast performance of the "Best model" and the "Best model excluding ESP." Chart 11 compares forecasts at different points in time, with the actual values. First, looking at the 2-month prior forecast values, those for both models are generally similar, and predict actual values for the second and third quarters of 2020 with high accuracy, when GDP moved significantly due to the impact of infectious diseases. The 1-month prior forecasts and forecasts at released date predict the actual values for the same period with more precision, and they are also able to capture movements in phases of the economy where the amplitude of GDP is large, such as the rush/rebound movements before and after the consumption tax rate hike in 2014 and 2019.

Next, we review the evolution of forecast errors before and after the spread of COVID-19 in Chart 12. The figure shows the RMSE from first quarter of 2013 to each subsequent time point. Concerning forecasts at release date and 1-month prior forecasts, the two Best models have almost the same RMSE as the Benchmark model, or have slightly larger RMSE compared with that of the Benchmark model. On the other hand, the Best model clearly has a better forecast for the 2-month prior forecast. This trend is particularly pronounced from 2020 onward, suggesting that the Best models, which utilizes alternative data and other data, are able to forecast values close to actual results at an early stage amid increasing volatility in economic fluctuations under the spread of COVID-19.

Finally, Charts 13 and 14 illustrate the evolution of the forecast values as data updates during the specific quarter, along with the contribution of each explanatory variable to the forecast values. Chart 13 illustrates the evolution of the forecasts in the third quarter of 2020. In this quarter, the nationwide public health measures to limit the spread of COVID-19 were lifted, resulting in a significant positive GDP growth rate of +5.3%. Meanwhile, at the 2-month prior to the release of GDP, both of the Best models forecast the higher 4% quarter-over-quarter range, close to the actual value. Looking at the contribution of each explanatory variable, alternative data (METIPOS and Google Trends) contribute to the convergence of the forecast value with the actual value. It can be seen that the contribution of ITA is relatively small, which means that ITA is extrapolated accurately by these alternative data. Similarly, looking at the evolution of the forecast values for the second quarter of 2021 in Chart 14, we can see that both Best models yield forecast values that are generally close to actual values with the aid of alternative data.

6. Concluding remarks

In this paper, we construct a new Bridge model incorporating alternative data (Google Trends and METIPOS) based on an existing nowcasting model, which uses only monthly and quarterly data. Using data through the first quarter of 2021, we also create a forecast combination model including new Bridge model by trying all possible candidate combinations and construct the nowcasting model with the lowest forecast error. Selected "Best models" improve the forecasting accuracy mainly for the 2-month prior forecast compared to the Benchmark model and enable us to nowcast GDP earlier and more accurately.

On the other hand, we have to remember that although the Benchmark model showed high forecasting performance prior to the spread of COVID-19, its accuracy has deteriorated since 2020. Just as with the Benchmark model, the Best models presented in this paper also may not be able to forecast GDP accurately as economic activity completely escapes the effects of COVID-19 and enters a new phase in the future. It is important to check and improve the model regularly to ensure that it is appropriate for the economic structure at any given time, rather than relying heavily on a specific model.

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Appendix. The details of extrapolation in the Bridge model

This supplement details the method of extrapolation of unpublished counts in the Bridge model, beyond the ITA described in Section 3. A summary of the economic variables used in the model construction is provided in the Appendix tables. The extrapolation method for the Benchmark model that serves as the baseline for this paper follows Chikamatsu et al. (2018). In selecting the Best models, we generally follow this Benchmark model and the extrapolation method of Chikamatsu et al. (2018), but some explanatory variables are changed based on the significance when the estimation period is extended to recent years.

(a) IIP

As equation (A1), we extrapolate unpublished counts of IIP (iip_t) using the result of survey of production forecast (mom change,$iipf_t$)[24].

$$iip_t = iipf_t \tag{A1}$$

(b) Economy Watchers Survey DI

As equation (A2), we extrapolate unpublished counts of Economy Watchers Survey (current condition, household-related DI,$watcher_t$) from IIP.

$$watcher_t = c + \beta_1 iip_t \tag{A2}$$

(c) Real sales values of wholesale industry

Real sales values of wholesale industry (csc_t) is estimated as an extrapolated value using IIP and the Economy Watchers Survey DI as explanatory variables (equation A3).

$$csc_t = c + \beta_1 iip_t + \beta_2 watcher_t \tag{A3}$$

(d) Real exports and real imports

Real exports (ex_t) are estimated using IIP as an explanatory variable, and real imports (im_t) are estimated using IIP and the Economy Watchers Survey DI as explanatory variables, and extrapolated values (equation A4 and A5).

$$ex_t = c + \beta_1 iip_t \tag{A4}$$

$$im_t = c + \beta_1 iip_t + \beta_2 watcher_t \tag{A5}$$

Note that if no explanatory data for the third month in a quarter are available and the extrapolation above is not possible, the counts for the third month in a quarter are calculated as the average of counts for the first and second months. In this case, if the actual data for the first and second months are not available, the extrapolated values shall be used.

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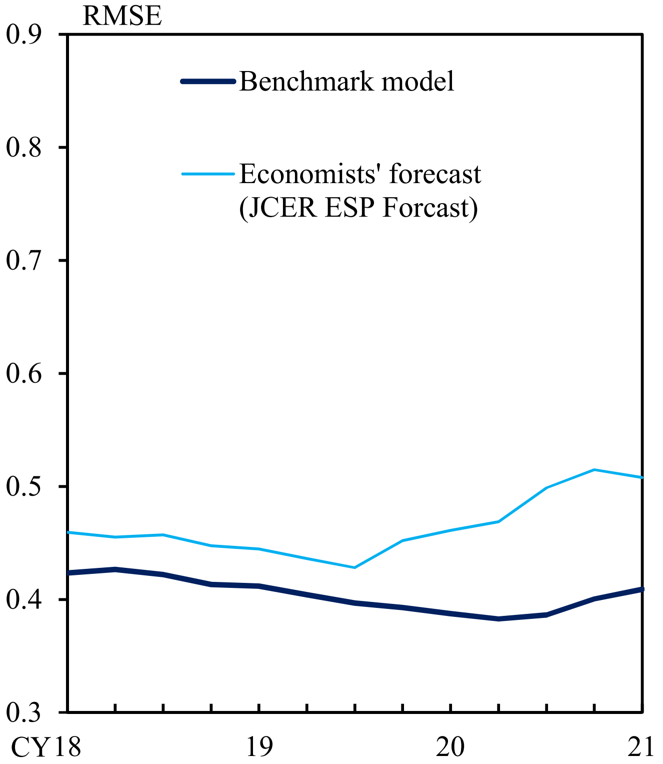
[24] For periods when indices in survey of production forecast are not available, IIP values are substituted.

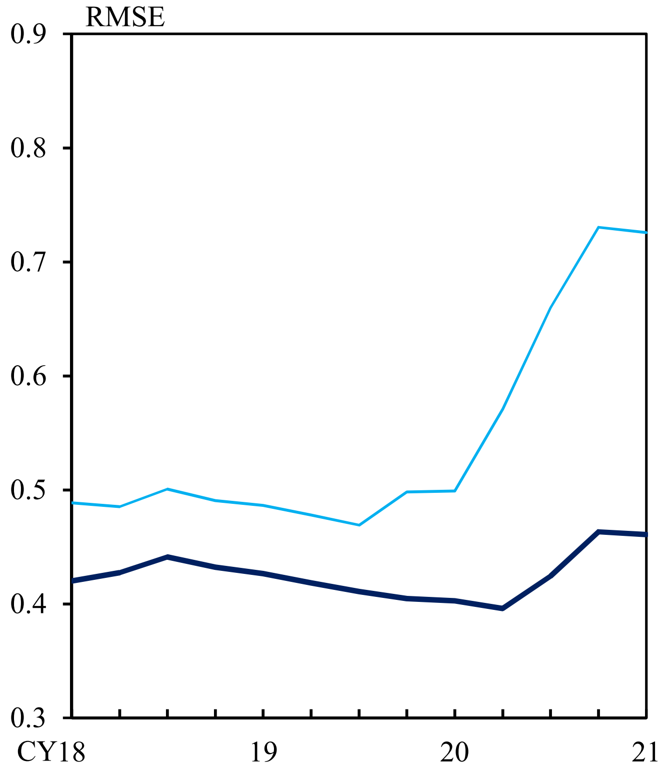
Chart 1

Forecast error of real GDP

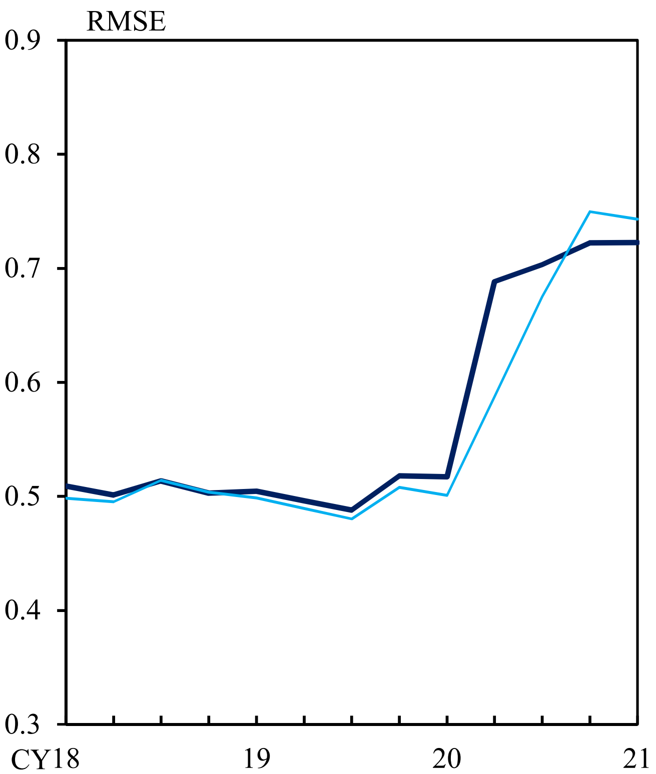
(1) Forecast at release date



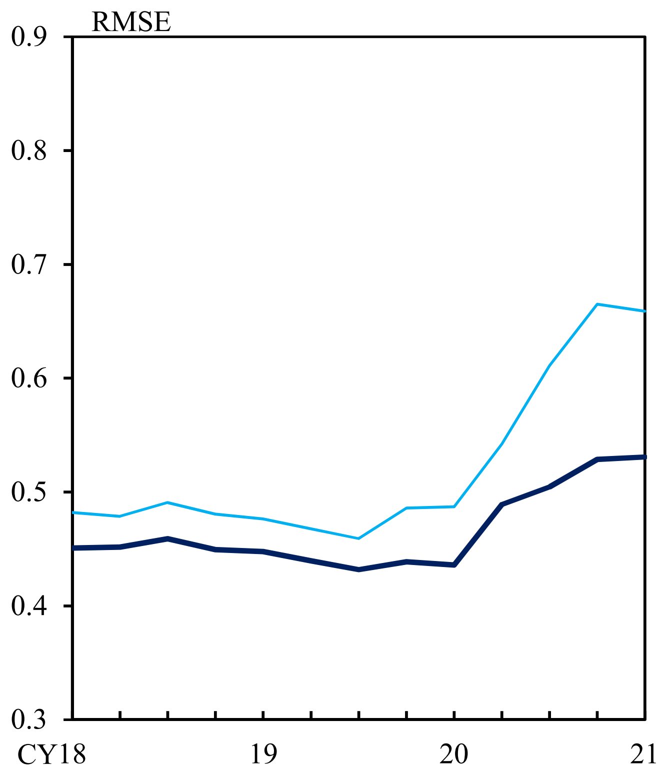
(2) Forecast at 1-month prior to release date



(3) Forecast at 2-month prior to release date



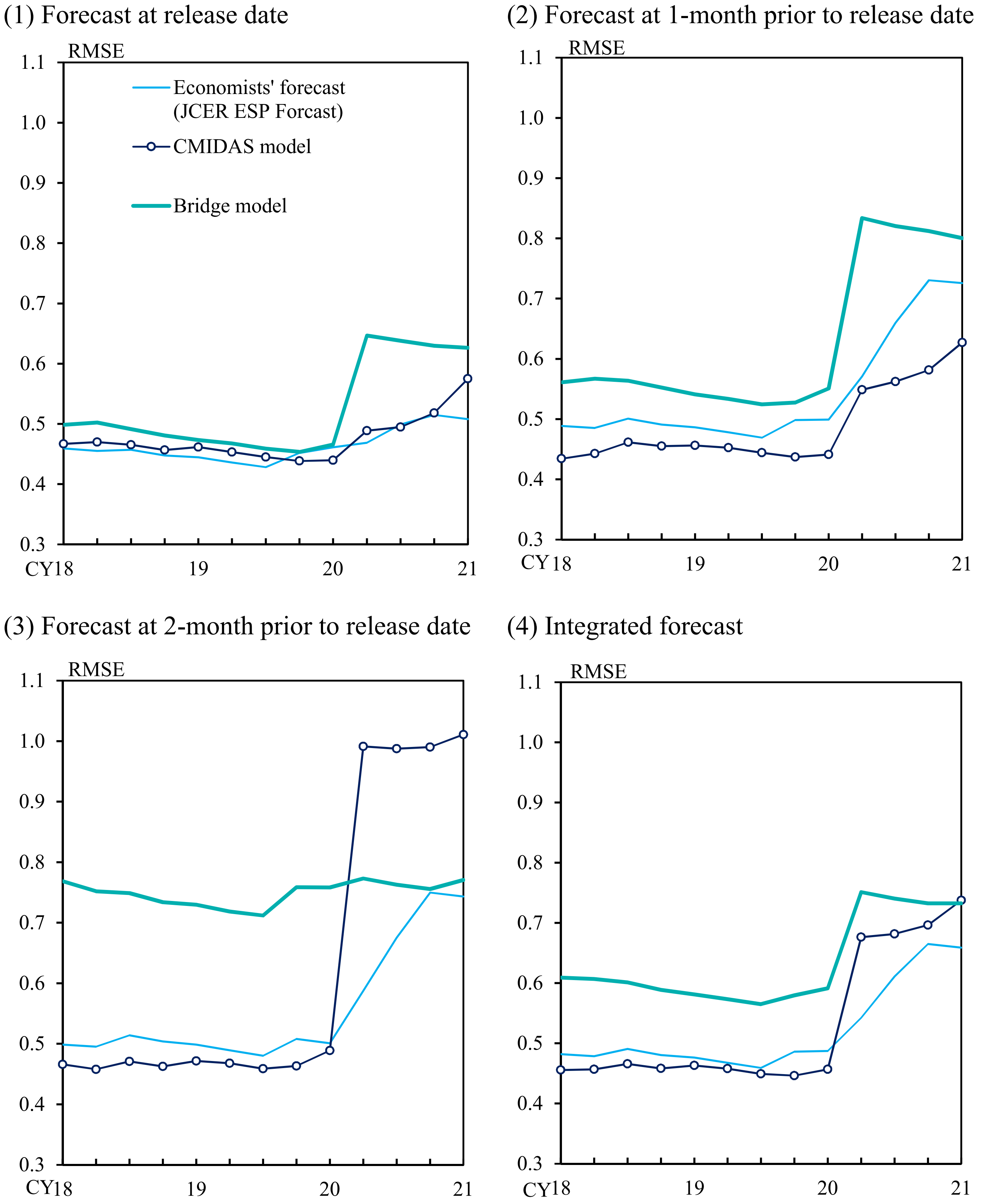
(4) Integrated forecast



Note: RMSE taken from 2013/Q1 and each data point.
Sources: Cabinet Office; Ministry of Economy, Trade and Industry; Bank of Japan;
Japan Center for Economic Research "ESP Forecast Survey"; Refinitiv Datastream.

Chart 2

Forecast error of real GDP for subcomponent of the Benchmark model

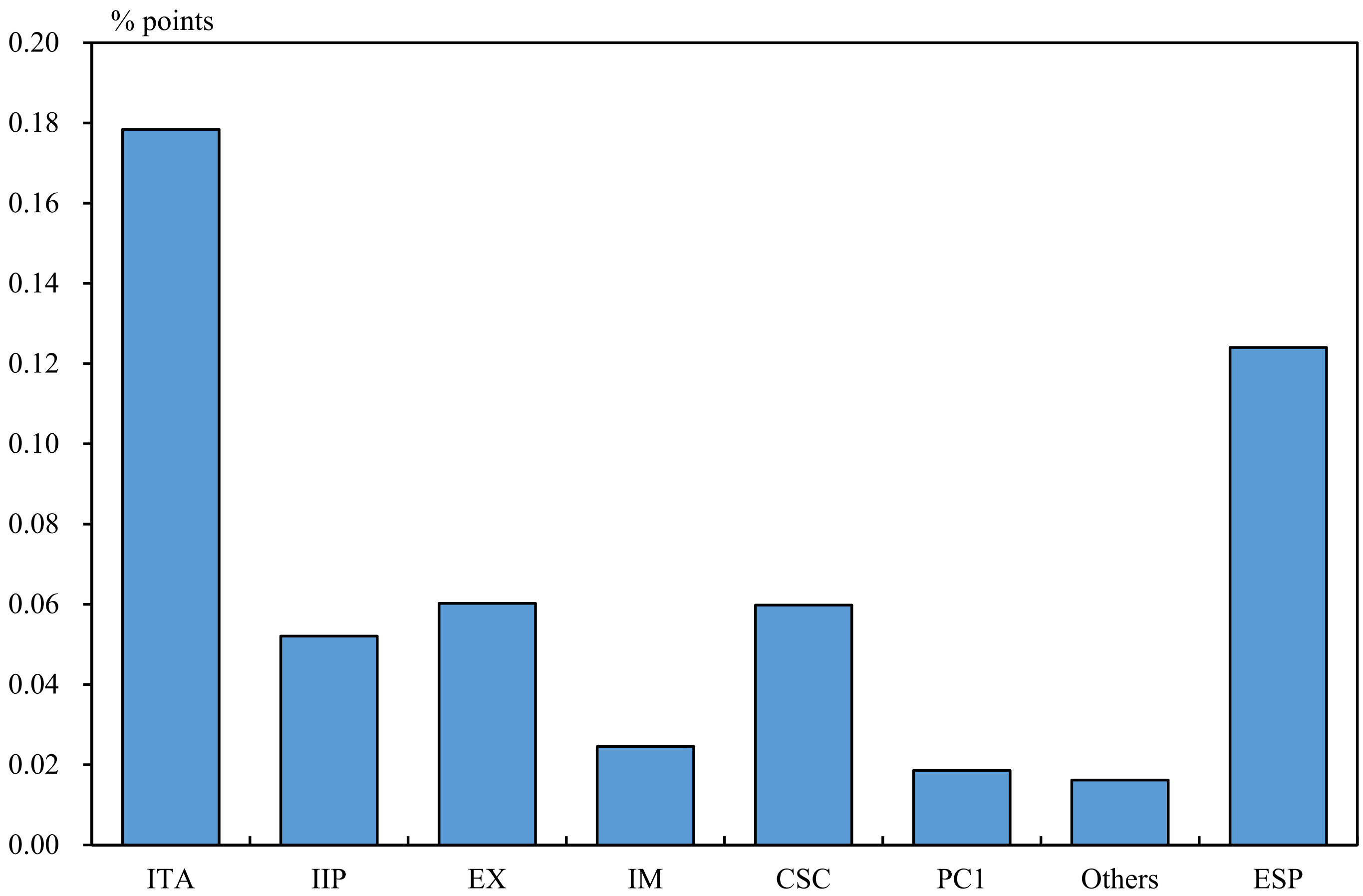


Note: RMSE taken from 2013/Q1 and each data point.
Sources: Cabinet Office; Ministry of Economy, Trade and Industry; Bank of Japan;
Japan Center for Economic Research "ESP Forecast Survey"; Refinitiv Datastream.

Chart 3

Contribution of each explanatory variable to the Benchmark model

Average contribution to the Benchmark model (absolute value)



Notes: 1. Figures show the absolute value of differences between the Benchmark model's forecast values before and after updating each variable's data. Averages taken from 2020/Q2 to 2021/Q1.

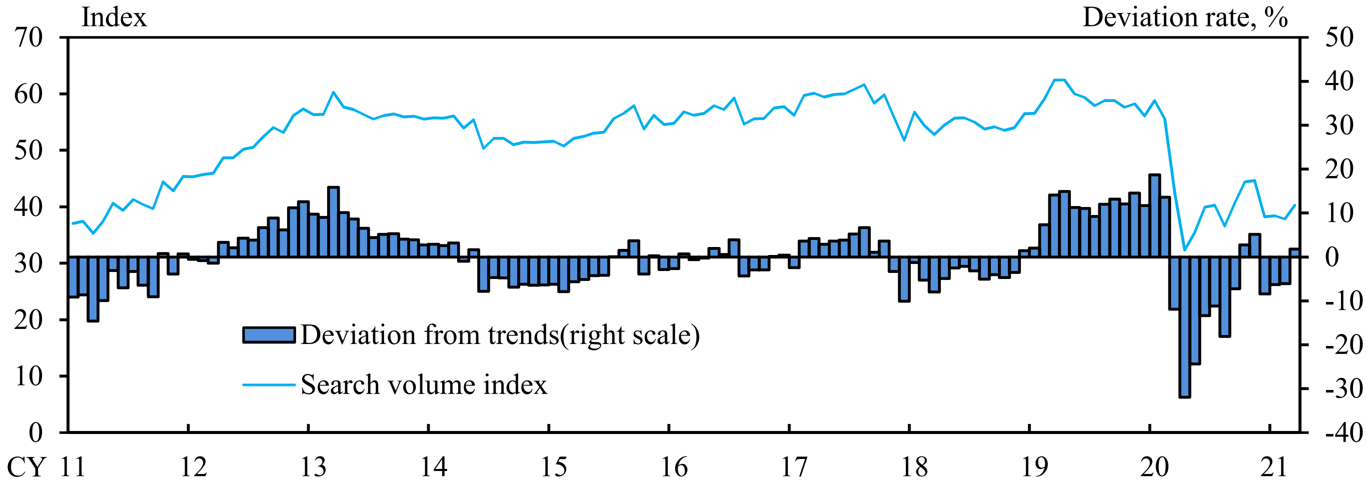
2. The labels are: ITA: index of tertiary industry activity; IIP: index of industrial production; EX: real exports; IM: real imports; CSC: real sales values of wholesale industry; PC1: Reuters *Tankan* Index (first principal component of subcomponents); and ESP: JCER ESP forecast.

3. "Others" includes the change of constant in the estimated equation.

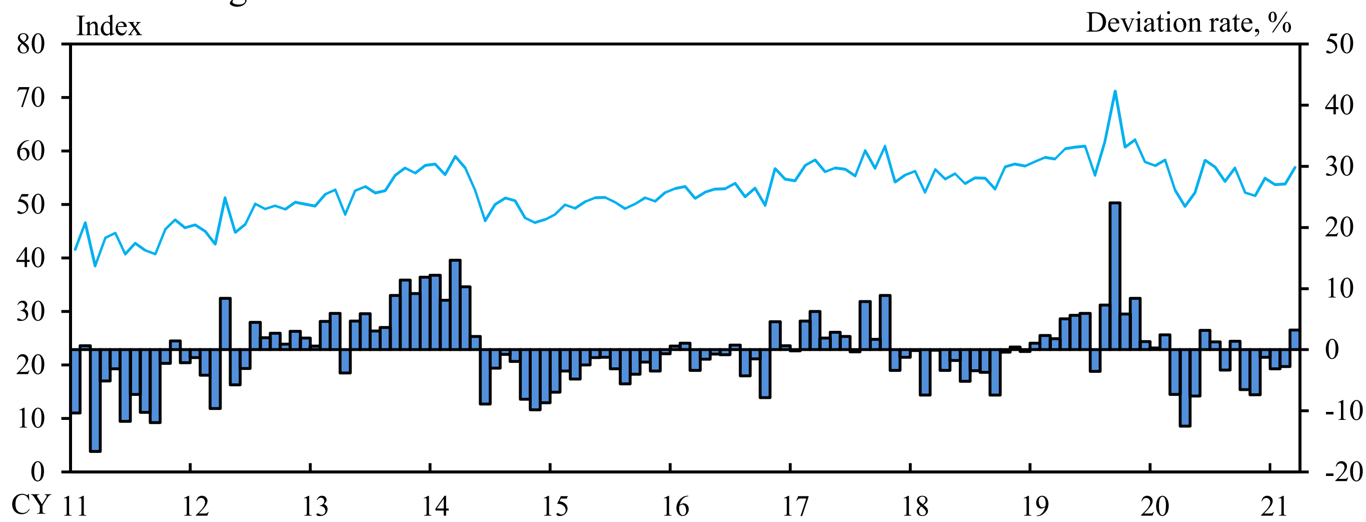
Sources: Cabinet Office; Ministry of Economy, Trade and Industry; Bank of Japan; Japan Center for Economic Research "ESP Forecast Survey"; Refinitiv Datastream.

Examples of Google Trends category search volume index

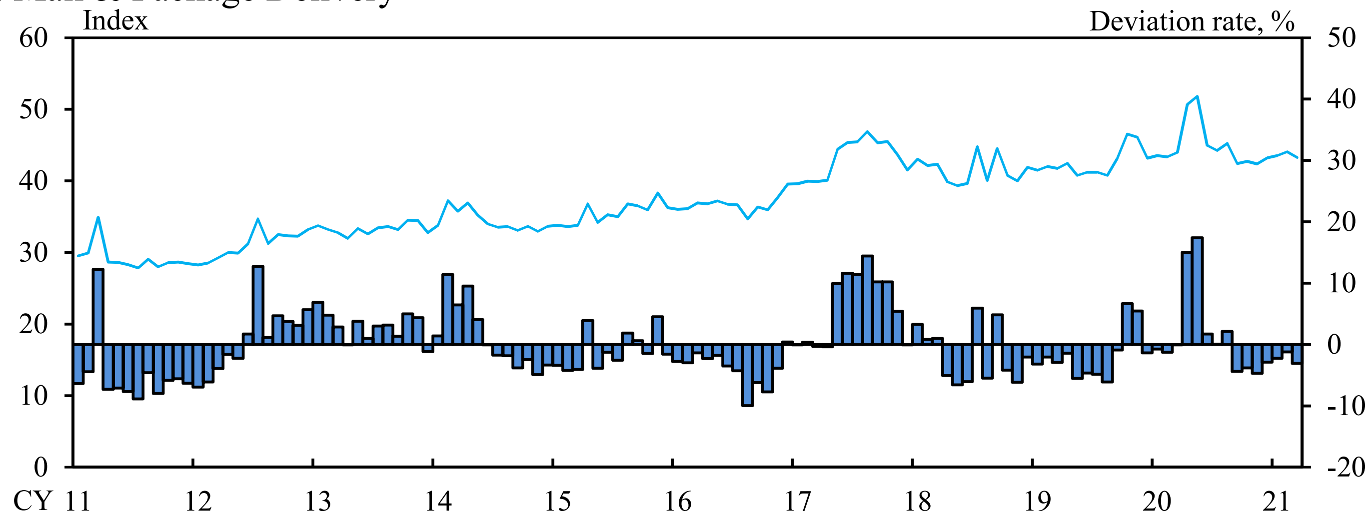
1. Travel Guides & Travelogues



2. Auto Financing



3. Mail & Package Delivery



Note: Trends are calculated using Hodrick-Prescott filter with the smoothing parameter 14,400.
Source: Google.

Extrapolation equation of ITA using Elastic net estimation (1)

rank	variables	coef.	rank	variables	coef.
1	**CSC**	**0.117**	59	OnlineGames	-
2	**CAR**	**0.047**	60	TVCommercials	-
3	**IIP**	**0.043**	61	Signage	-
4	METIPOS(Convenience store)	0.041	62	Timeshares&VacationProperties	-
5	METIPOS(Home improvement store)	0.037	63	FilmFestivals	-
6	METIPOS(Drug store)	0.035	64	MobileApps&Add-Ons	-
7	TravelGuides&Travelogues	0.023	65	RecordingIndustry	-
8	Plastics&Polymers	0.019	66	Film&TVIndustry	-
9	**Watcher**	**0.019**	67	BusinessFinance	-
10	AutoFinancing	0.016	68	Boats&Watercraft	-
11	HomeFinancing	0.013	69	WebApps&OnlineTools	-
12	Optoelectronics&Fiber	0.013	70	PersonalAircraft	-
13	CarRental&TaxiServices	0.012	71	CommercialLending	-
14	InvestmentBanking	0.012	72	Consulting	-
15	Uniforms&Workwear	0.012	73	CarElectronics	-
16	PropertyInspections&Appraisals	0.010	74	AutomotiveIndustry	-
17	Headwear	0.009	75	Bicycles&Accessories	-
18	Distribution&Logistics	0.009	76	SwapMeets&OutdoorMarkets	-
19	CasualApparel	0.008	77	Campers&RVs	-
20	TouristDestinations	0.007	78	CommercialVehicles	-
21	HealthInsurance	0.006	79	Engine&Transmission	-
22	EventPlanning	0.006	80	AutoExterior	-
23	METIPOS(Large electronics retail store)	0.006	81	AutoInterior	-
24	VehicleFuels&Lubricants	0.005	82	CosmeticProcedures	-
25	Outsourcing	0.005	83	Wholesalers&Liquidators	-
26	TravelAgencies&Services	0.005	84	TobaccoProducts	-
27	Mobile&WirelessAccessories	0.005	85	VehicleSpecs,Reviews&Comparisons	-
28	Bed&Bath	0.005	86	Parking	-
29	Scooters&Mopeds	0.005	87	Microcars&CityCars	-
30	Printing&Publishing	0.004	88	Carpooling&Ridesharing	-
31	UrbanTransport	0.004	89	PublicStorage	-
32	ApparelServices	0.004	90	WaterSupply&Treatment	-
33	Hotels&Accommodations	0.004	91	Art&CraftSupplies	-
34	ClothingAccessories	0.003	92	Laundry	-
35	ElectronicComponents	0.003	93	Homemaking&InteriorDecor	-
36	LiveSportingEvents	0.003	94	Spas&BeautyServices	-
37	Commercial&InvestmentRealEstate	0.003	95	HairCare	-
38	AthleticApparel	0.003	96	Off-RoadVehicles	-
39	FuelEconomy&GasPrices	0.003	97	HomeImprovement	-
40	Electricity	0.002	98	Fashion&Style	-
41	Holidays&SeasonalEvents	0.002	99	AirTravel	-
42	RealEstateListings	0.002	100	Cruises&Charters	-
43	Test&Measurement	0.002	101	SoftwareUtilities	-
44	Coffee&Tea	0.002	102	WeightLoss	-
45	PropertyDevelopment	0.001	103	Pharmacy	-
46	Oil&Gas	0.001	104	Hospitals&TreatmentCenters	-
47	DiningGuides	0.001	105	Pharmaceuticals&Biotech	-
48	Eyewear	0.001	106	SportingGoods	-
49	InternetSoftware	0.001	107	HomeFurnishings	-
50	Resumes&Portfolios	0.001	108	IndustrialMaterials&Equipment	-
51	Investing	0.001	109	Freight&Trucking	-
52	MovieListings&TheaterShowtimes	0.001	110	Packaging	-
53	FormalWear	0.000	111	Moving&Relocation	-
54	KnowledgeManagement	0.000	112	Weddings	-
55	Luggage&TravelAccessories	-	113	OperatingSystems	-
56	SpecialtyTravel	-	114	DesktopComputers	-
57	ClassicVehicles	-	115	ComputerPeripherals	-
58	ISPs	-	116	E-CommerceServices	-

Notes: 1. Figures based on the estimation whose sample period is from November 2011 to March 2021.

2. Variables, except alternative data, are in bold (Watcher: Economy Watchers Survey DI for current conditions; CAR: new passenger car registrations; CSC: real sales values of wholesale industry; and IIP: index of industrial production). The variable name denotes the category name of Google Trends search volume index unless otherwise specified.

3. - indicates that corresponding coefficient is estimated as zero by sparse estimation.

Sources: Cabinet Office; Ministry of Economy, Trade and Industry; Bank of Japan; Google; Japan Automobile Dealers Association; Japan Mini Vehicle Association.

Extrapolation equation of ITA using Elastic net estimation (2)

rank	variables	coef.
117	Import&Export	-
118	Gadgets&PortableElectronics	-
119	Apartments&ResidentialRentals	-
120	PhoneServiceProviders	-
121	CommunicationsEquipment	-
122	MobilePhones	-
123	Beer	-
124	Wine	-
125	Liquor	-
126	Magazines	-
127	Bankruptcy	-
128	Toys	-
129	VehicleWheels&Tires	-
130	Photographic&DigitalArts	-
131	Cycling	-
132	HomeInsurance	-
133	AutoInsurance	-
134	ComputerDrives&Storage	-
135	MultimediaSoftware	-
136	Business&ProductivitySoftware	-
137	Cable&SatelliteProviders	-
138	ShoppingPortals&SearchEngines	-
139	SmallBusiness	-
140	Pets	-
141	Textiles&Nonwovens	-
142	Webcams&VirtualTours	-
143	Photo&VideoServices	-
144	E-Books	-
145	Trucks&SUVs	-
146	TicketSales	-
147	BuildingMaterials&Supplies	-
148	CivilEngineering	-
149	ConstructionConsulting&Contracting	-
150	Renewable&AlternativeEnergy	-
151	Aviation	-
152	MaritimeTransport	-
153	RailTransport	-
154	Agrochemicals	-
155	Coatings&Adhesives	-
156	Dyes&Pigments	-
157	Outdoors	-
158	LuxuryGoods	-
159	Footwear	-
160	Welfare&Unemployment	-
161	Bus&Rail	-
162	ComputerComponents	-
163	PhysicalAssetManagement	-
164	QualityControl&Tracking	-
165	Writing&EditingServices	-
166	ComputerServers	-
167	HardwareModding&Tuning	-
168	EnterpriseTechnology	-
169	EducationalSoftware	-
170	Custom&PerformanceVehicles	-
171	Hybrid&AlternativeVehicles	-
172	CreditCards	-
173	DebtManagement	-
174	CollegeFinancing	-

rank	variables	coef.
175	Currencies&ForeignExchange	-
176	VehicleBrands	-
177	RetailTrade	-
178	AnimalProducts&Services	-
179	Concerts&MusicFestivals	-
180	GameSystems&Consoles	-
181	Freeware&Shareware	-
182	VentureCapital	-
183	Poker&CasinoGames	-
184	Kitchen&Dining	-
185	NuclearEnergy	-
186	FoodService	-
187	CareerResources&Planning	-
188	JobListings	-
189	Costumes	-
190	Men'sClothing	-
191	Outerwear	-
192	Sleepwear	-
193	Women'sClothing	-
194	RecreationalAviation	-
195	METIPOS(Supermarket)	-
196	CorporateEvents	-0.000
197	TV&VideoEquipment	-0.000
198	CleaningAgents	-0.001
199	Swimwear	-0.001
200	Undergarments	-0.001
201	HomeStorage&Shelving	-0.001
202	Doctors'Offices	-0.002
203	Fire&SecurityServices	-0.002
204	Urban&RegionalPlanning	-0.002
205	WebPortals	-0.003
206	Metals&Mining	-0.004
207	Housing&Development	-0.004
208	Nursery&Playroom	-0.004
209	PowerSupplies	-0.006
210	BookRetailers	-0.006
211	DataSheets&ElectronicsReference	-0.006
212	DomesticServices	-0.006
213	TVShows&Programs	-0.006
214	RiskManagement	-0.006
215	EntertainmentMedia	-0.009
216	Candy&Sweets	-0.009
217	ElectronicAccessories	-0.009
218	ElectromechanicalDevices	-0.010
219	Children'sClothing	-0.010
220	PropertyManagement	-0.011
221	Laptops&Notebooks	-0.012
222	FastFood	-0.013
223	WasteManagement	-0.019
224	Mail&PackageDelivery	-0.022
225	HomeAppliances	-0.022
226	OnlineVideo	-0.022
	Constant	-0.893

Calibrated hyperparameter

λ	0.100
α	0.200

Notes: 1. Figures based on the estimation whose sample period is from November 2011 to March 2021.

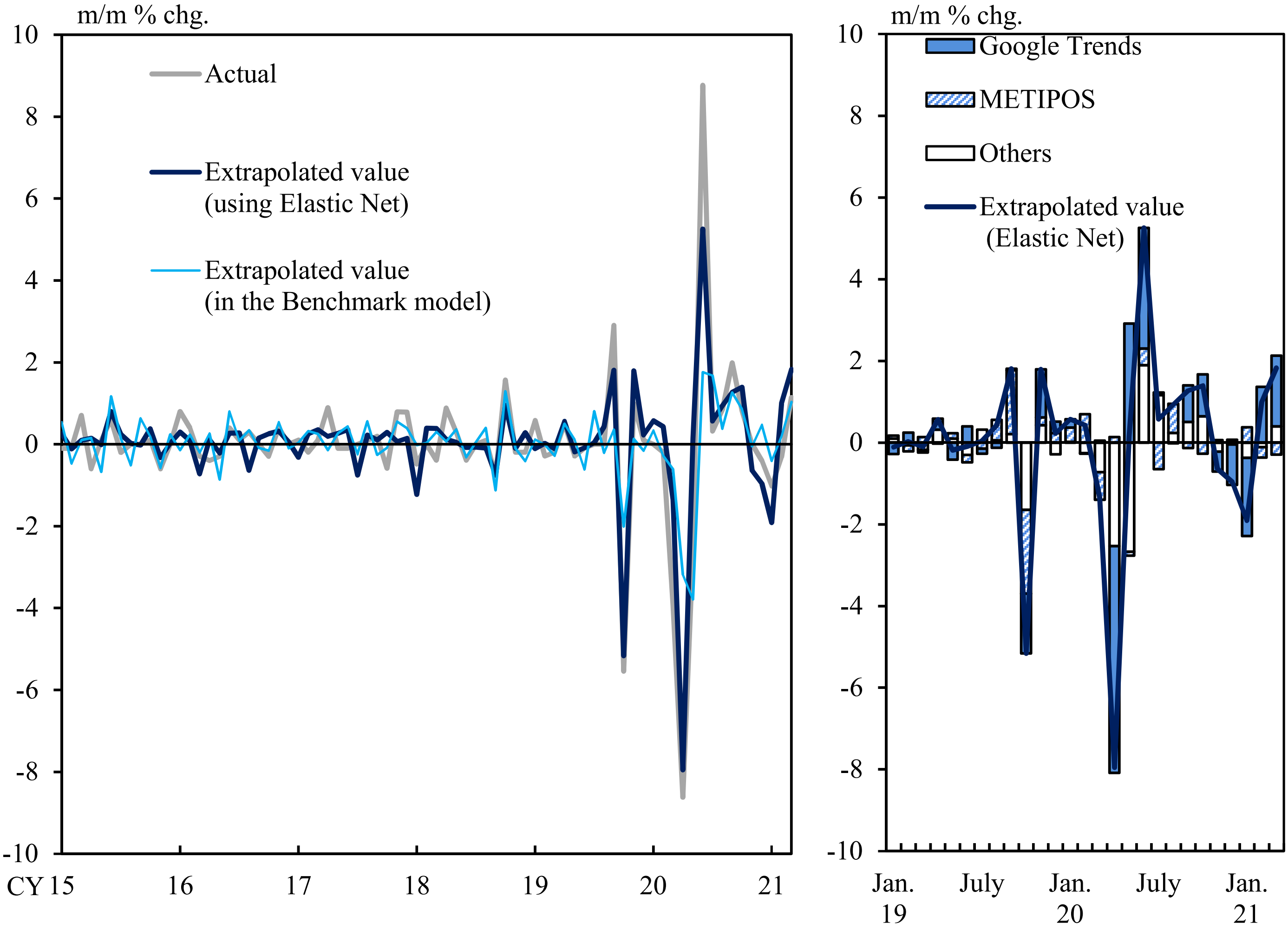
2. Variables, except alternative data, are in bold (Watcher: Economy Watchers Survey DI for current conditions; CAR: new passenger car registrations; CSC: real sales values of wholesale industry; and IIP: index of industrial production). The variable name denotes the category name of Google Trends search volume index unless otherwise specified.

3. - indicates that corresponding coefficient is estimated as zero by sparse estimation.

Sources: Cabinet Office; Ministry of Economy, Trade and Industry; Bank of Japan; Google; Japan Automobile Dealers Association; Japan Mini Vehicle Association.

Extrapolation performance of ITA

(1) Extrapolated value of ITA, the decomposition of extrapolated value

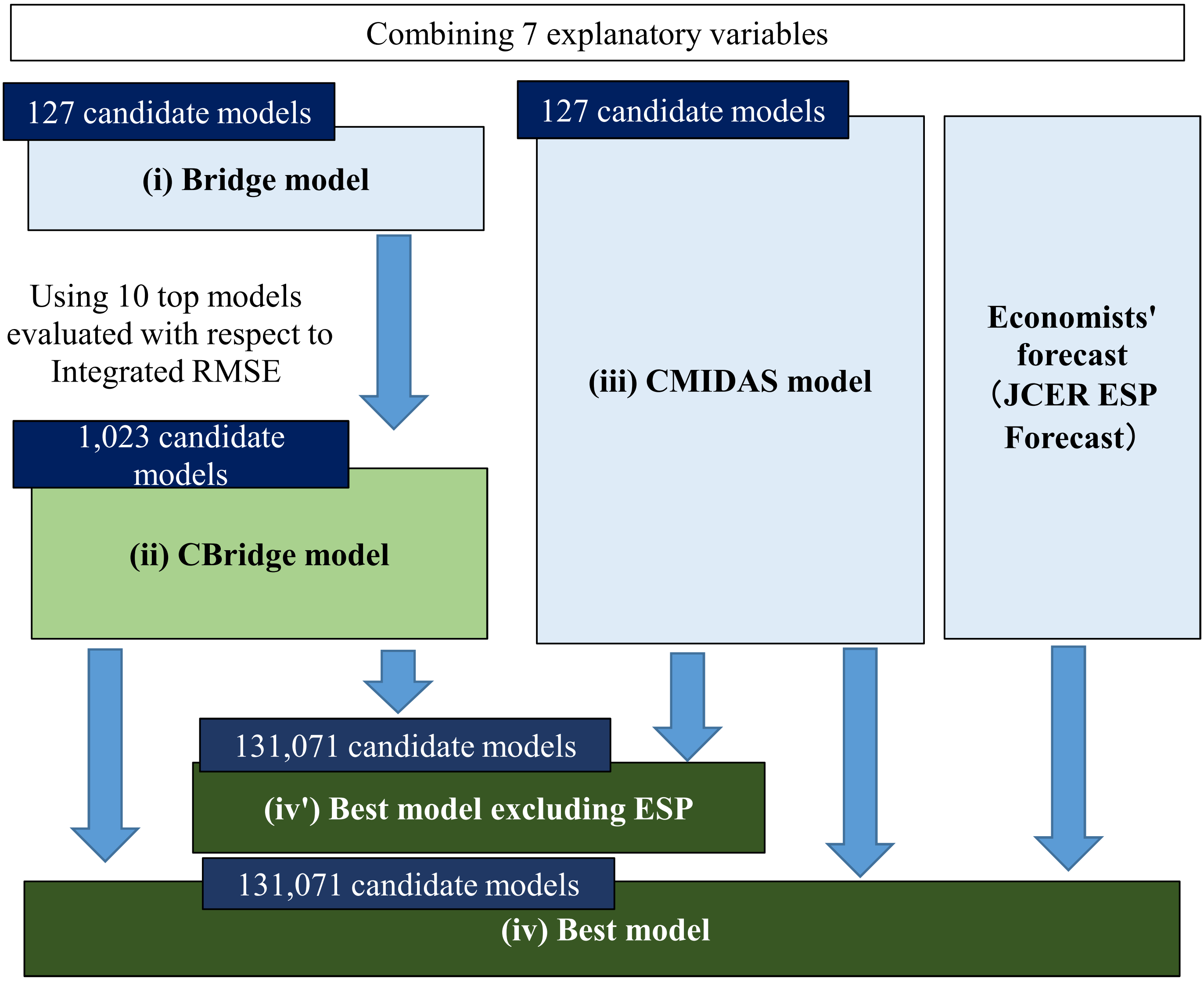


(2) Extrapolated performance (RMSE)

	Jan. 2015 - Mar. 2021	Jan. 2015 - Dec. 2019	Jan. 2020 - Mar. 2021
Extrapolated value (using Elastic Net)	0.77	0.46	1.47
Extrapolated value (in the Benchmark model)	1.30	0.72	2.52

Note: Extrapolated values for each month are estimated using data available immediately before ITA released.
Sources: Cabinet Office; Ministry of Economy, Trade and Industry; Bank of Japan; Google; Japan Automobile Dealers Association; Japan Mini Vehicle Association.

Summary of model selection procedure



Result of model selection (1)

(1) Benchmark model

	RMSE			
	Integrated	At release date	At 1-month prior	At 2-month prior
Benchmark model	0.531	0.409	0.461	0.723

(2) Bridge model (10 best spec evaluated with Integrated RMSE)

Rank	Explanatory variables	RMSE			
		Integrated	At release date	At 1-month prior	At 2-month prior
1	ITA EX Watcher CAR	0.494	0.444	0.506	0.534
2	ITA EX CAR	0.495	0.450	0.511	0.525
3	ITA EX Watcher	0.501	0.443	0.496	0.566
4	ITA EX	0.502	0.447	0.498	0.560
5	ITA EX IM CSC CAR	0.514	0.482	0.537	0.522
6	ITA EX IM CSC Watcher CAR	0.517	0.483	0.540	0.527
7	ITA EX CSC Watcher	0.517	0.454	0.519	0.579
8	ITA EX CSC	0.517	0.454	0.520	0.578
9	ITA EX IM Watcher CAR	0.519	0.486	0.526	0.546
10	ITA EX IM CSC	0.525	0.485	0.528	0.561

(3) CBridge model (10 best spec evaluated with Integrated RMSE)

Rank	Combined models	RMSE			
		Integrated	At release date	At 1-month prior	At 2-month prior
1	BR1 BR2 BR3 BR5 BR9	0.489	0.445	0.500	0.521
2	BR1 BR3 BR5 BR9	0.489	0.445	0.499	0.522
3	BR1 BR3 BR5	0.489	0.442	0.500	0.526
4	BR1 BR2 BR3 BR9	0.489	0.442	0.496	0.529
5	BR1 BR2 BR3 BR4 BR5 BR9	0.489	0.443	0.498	0.526
6	BR1 BR2 BR9	0.489	0.447	0.500	0.521
7	BR1 BR3 BR4 BR5 BR9	0.489	0.444	0.497	0.528
8	BR1 BR2 BR4 BR5 BR9	0.489	0.446	0.501	0.521
9	BR1 BR4 BR5	0.490	0.443	0.501	0.525
10	BR1 BR3 BR4 BR5	0.490	0.440	0.497	0.532

Notes: 1. RMSE are taken from 2013/Q1 to 2021/Q1 .
2. The explanatory variables in (2) are as follows: ITA: index of tertiary industry activity; EX: real exports; IM: real imports; Watcher: Economy Watchers Survey DI for current conditions; CAR: new passenger car registrations; and CSC: real sales values of wholesale industry.
3. BRX in (3) denotes the Xth best Bridge model in (2).

Result of model selection (2)

(1) CMIDAS model (10 best spec evaluated with Integrated RMSE)

Rank	Explanatory variables	RMSE			
		Integrated	At release date	At 1-month prior	At 2-month prior
1	CSC IIP ITA EX Watcher CAR	0.643	0.530	0.575	0.825
2	CSC IIP ITA EX IM Watcher CAR	0.646	0.537	0.578	0.824
3	CSC IIP ITA EX Watcher	0.652	0.501	0.559	0.894
4	CSC IIP ITA EX IM Watcher	0.665	0.515	0.574	0.905
5	CSC IIP ITA Watcher	0.676	0.510	0.602	0.917
6	IIP ITA EX IM Watcher CAR	0.677	0.520	0.614	0.896
7	IIP ITA EX Watcher CAR	0.678	0.518	0.623	0.892
8	CSC IIP ITA Watcher CAR	0.685	0.550	0.634	0.872
9	IIP ITA EX Watcher	0.688	0.495	0.602	0.968
10	CSC IIP ITA EX CAR	0.689	0.558	0.577	0.931

(2) Selection of Best model (5 best spec evaluated with Integrated RMSE)

Rank	Combined models or Forecasts	RMSE			
		Integrated	At release date	At 1-month prior	At 2-month prior
1	COMBR1022 ESP	**0.484**	**0.406**	**0.509**	**0.537**
2	COMBR990 ESP	0.485	0.406	0.512	0.537
3	COMBR1008 ESP	0.485	0.404	0.510	0.541
4	COMBR1019 ESP	0.485	0.403	0.508	0.544
5	COMBR1012 ESP	0.488	0.406	0.513	0.544

(3) Selection of Best model excluding ESP (5 best spec evaluated with Integrated RMSE)

Rank	Combined models	RMSE			
		Integrated	At release date	At 1-month prior	At 2-month prior
1	COMBR1	**0.48876**	**0.445**	**0.500**	**0.521**
2	COMBR2	0.48883	0.445	0.499	0.522
3	COMBR3	0.489	0.442	0.500	0.526
4	COMBR4	0.489	0.442	0.496	0.529
5	COMBR5	0.489	0.443	0.498	0.526

Notes: 1. RMSE are taken from 2013/Q1 to 2021/Q1 .
2. The explanatory variables in (1) are as follows: ITA: index of tertiary industry activity; EX: real exports; IM: real imports; Watcher: Economy Watchers Survey DI for current conditions; CAR: new passenger car registrations; CSC: real sales values of wholesale industry; and IIP: index of industrial production.
3. COMBRX in (2) and (3) denotes the Xth best CBridge model evaluated with integrated RMSE. ESP denotes JCER ESP forecast.

Chart 10

Specification of selected Best models

Best model

The simple average of one Bridge model forecast and ESP forecast.

<Combined Forecasts>

1. Bridge model using ITA, EX, IM, Watcher, CAR
2. JCER ESP forecast

Best model excluding ESP

The simple average of 5 Bridge model forecasts.

<Combined Forecasts>

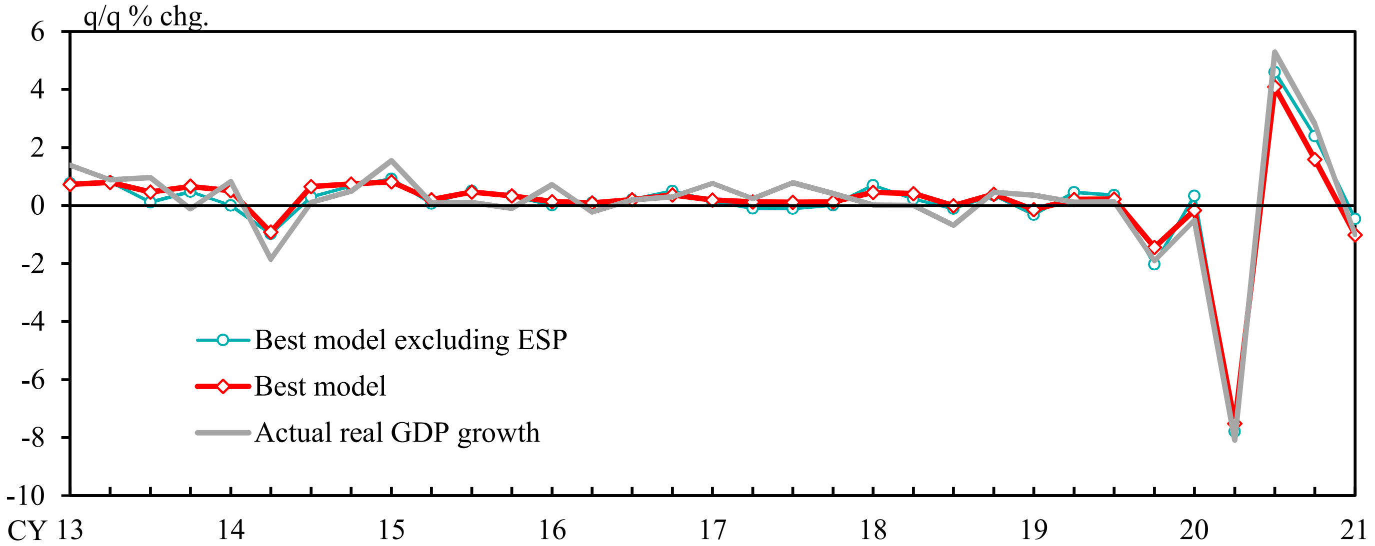
1. Bridge model using ITA, EX, Watcher, CAR
2. Bridge model using ITA, EX, CAR
3. Bridge model using ITA, EX, Watcher
4. Bridge model using ITA, EX, IM, CSC, CAR
5. Bridge model using ITA, EX, IM, Watcher, CAR

Note: The explanatory variables are as follows. ITA: index of tertiary industry activity; EX: real exports; IM: real imports; Watcher: Economy Watchers Survey DI for current conditions; CAR: new passenger car registrations; and CSC: real sales values of wholesale industry.

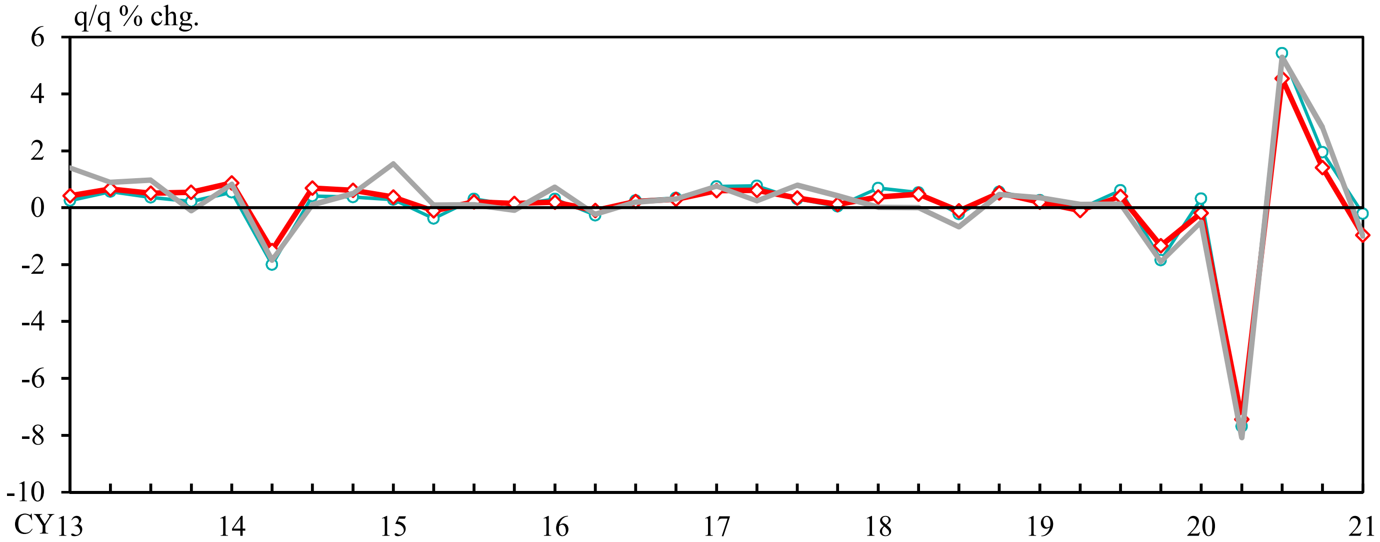
Chart 11

Best models' forecasts

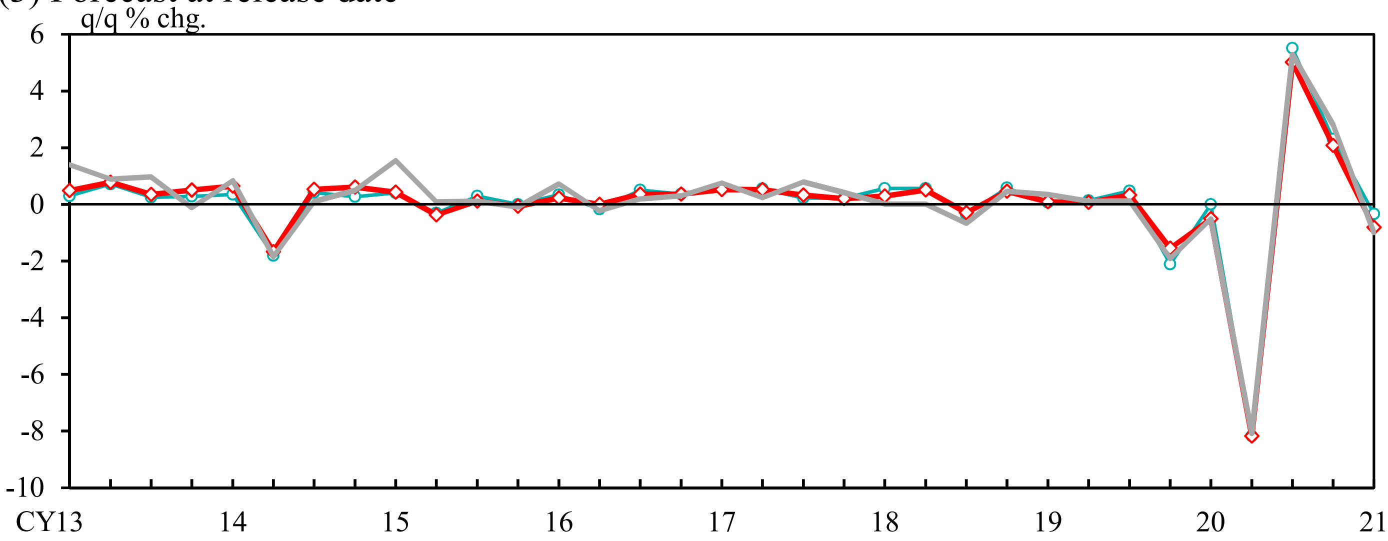
(1) Forecast at 2-month prior to release date



(2) Forecast at 1-month prior to release date

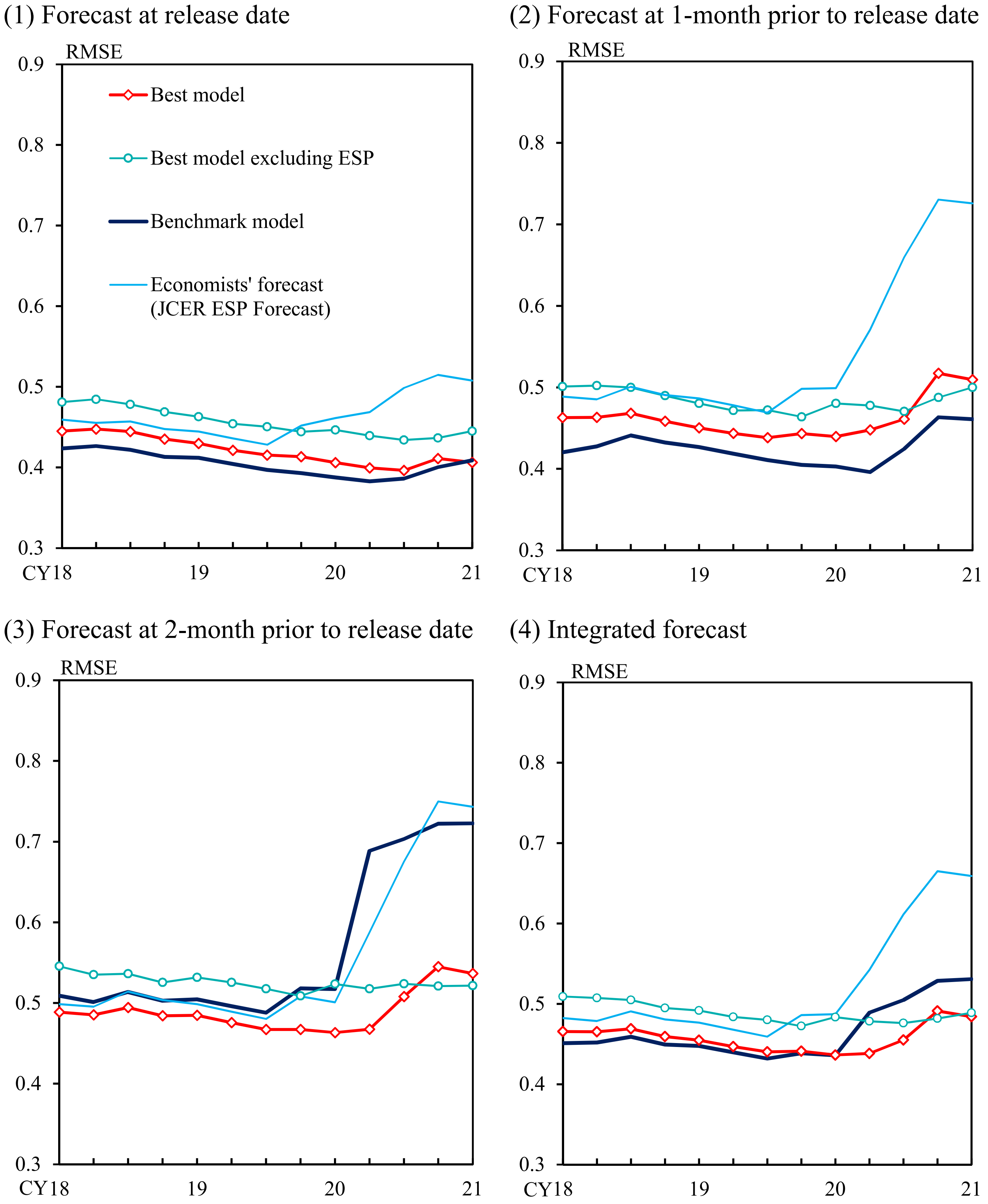


(3) Forecast at release date



Sources: Cabinet Office; Ministry of Economy, Trade and Industry; Bank of Japan; Japan Center for Economic Research "ESP Forecast Survey"; Google; Japan Automobile Dealers Association; Japan Mini Vehicle Association.

Forecast Error of Real GDP



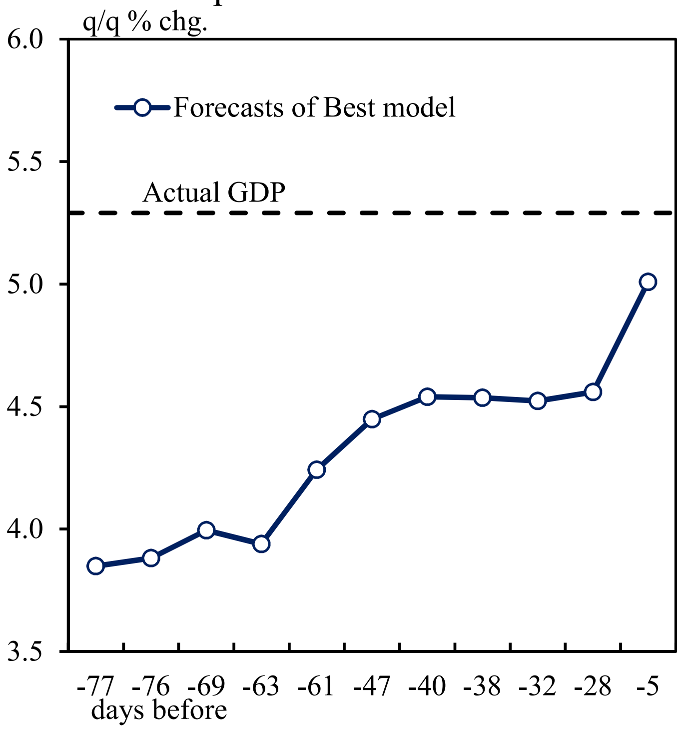
Note: RMSE taken from 2013/Q1 and each data point.

Sources: Cabinet Office; Ministry of Economy, Trade and Industry; Bank of Japan; Japan Center for Economic Research "ESP Forecast Survey"; Refinitiv Datastream; Google; Japan Automobile Dealers Association; Japan Mini Vehicle Association.

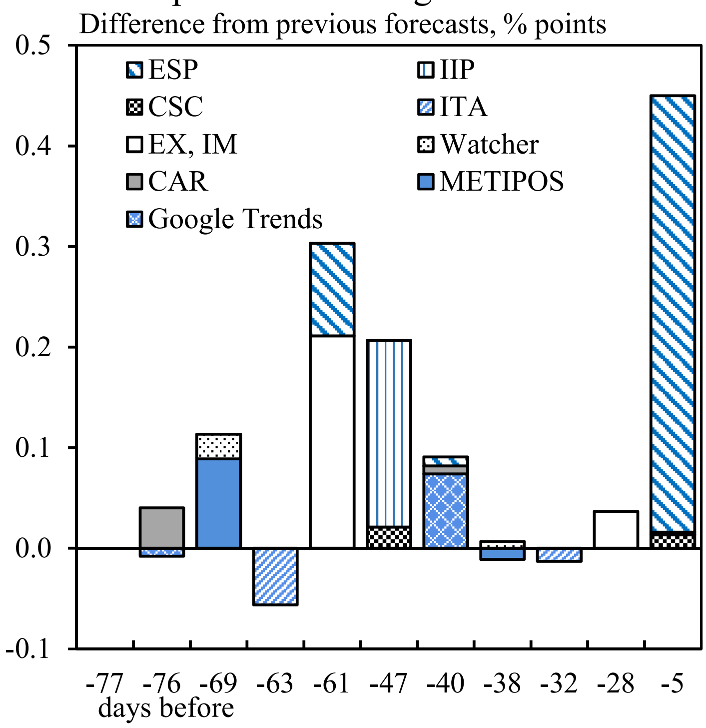
Historical path of Best models' forecasts (2020/Q3)

(1) Best model

1. Historical path of forecasts

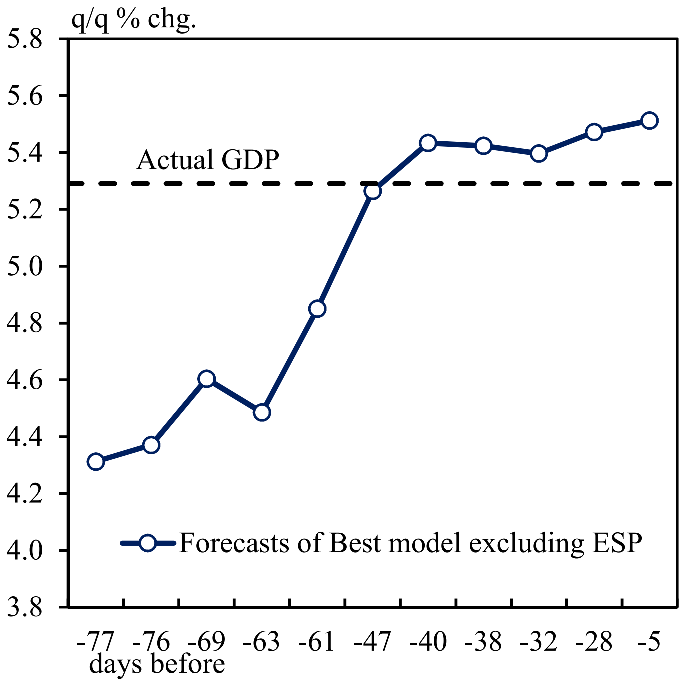


2. Decomposition of changes in forecasts

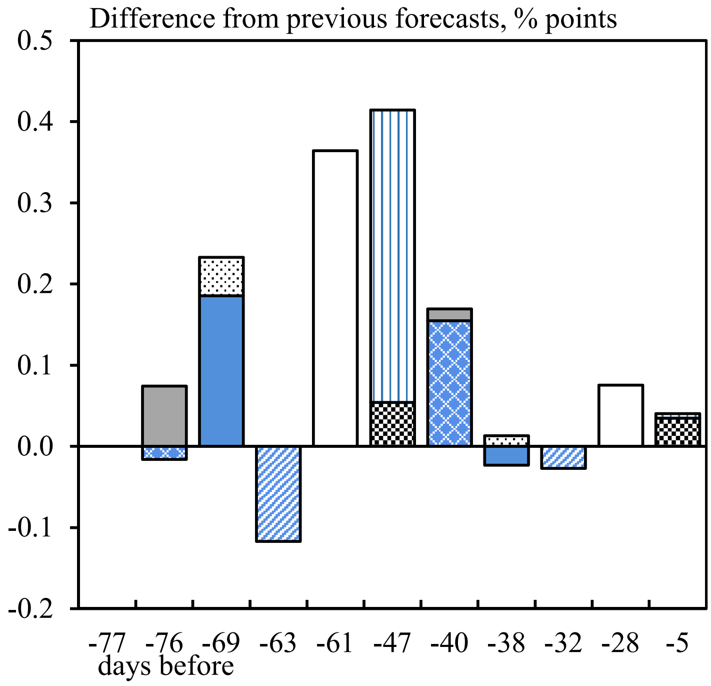


(2) Best model excluding ESP

1. Historical path of forecasts



2. Decomposition of changes in forecasts



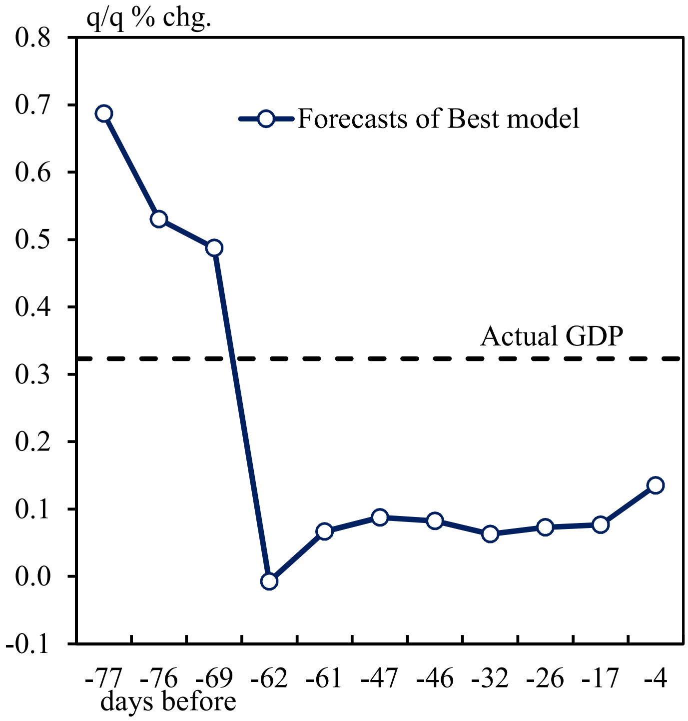
Notes: 1. The horizontal axes show the number of days until first preliminary estimate of official GDP releases.
2. The contribution of each dependent variable to forecasts is defined as difference between the forecast before the data reflects and after the data reflects. Therefore, it contains the effect of estimated coefficient changes.
3. Google Trends and METIPOS are reflected to forecasts after their monthly data become available.

Sources: Cabinet Office; Ministry of Economy, Trade and Industry; Bank of Japan; Japan Center for Economic Research "ESP Forecast Survey"; Google; Japan Automobile Dealers Association; Japan Mini Vehicle Association.

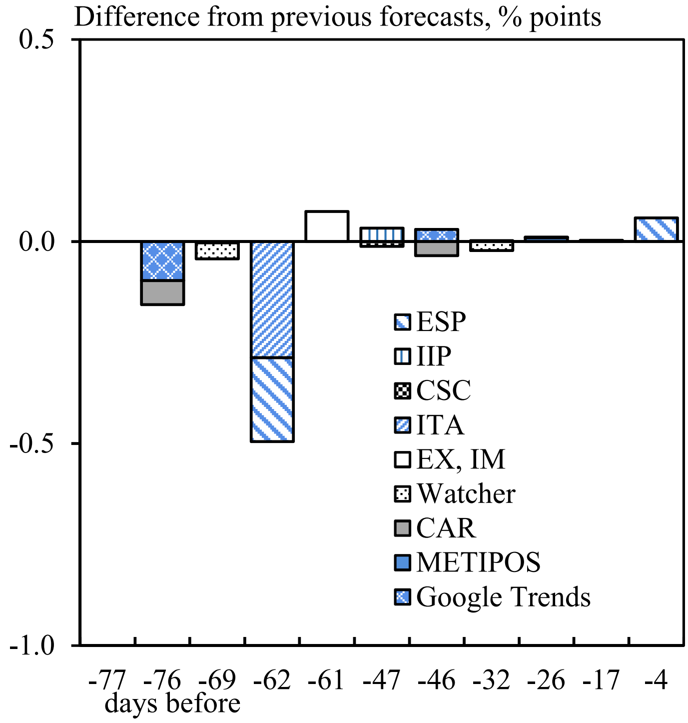
Historical path of Best models' forecasts (2021/Q2)

(1) Best model

1. Historical path of forecasts

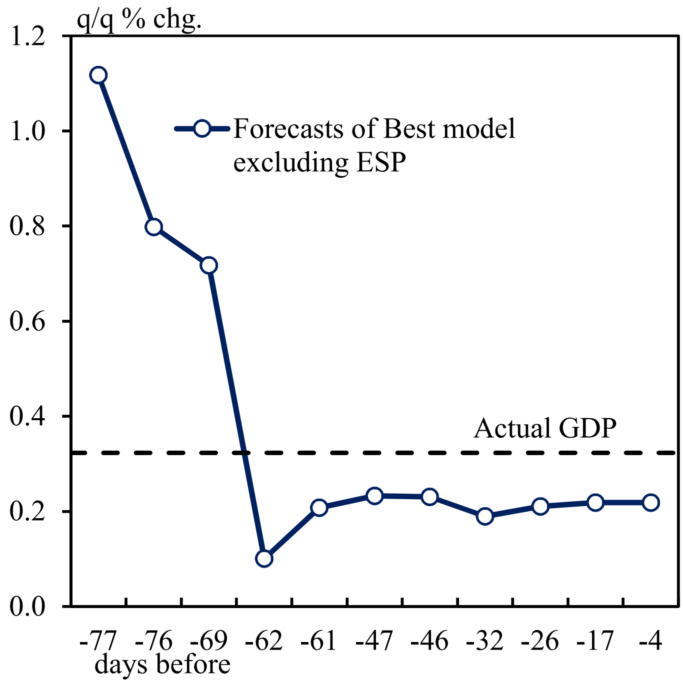


2. Decomposition of changes in forecasts

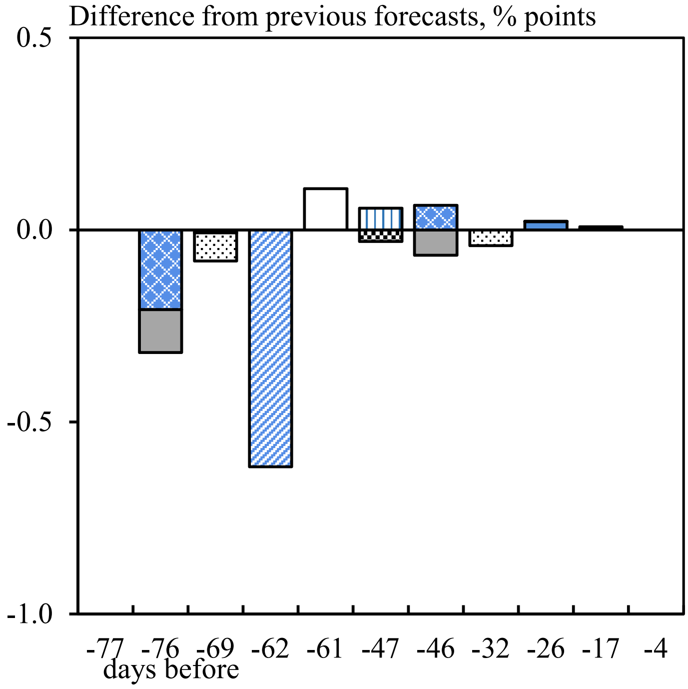


(2) Best model excluding ESP

1. Historical path of forecasts



2. Decomposition of changes in forecasts



Notes: 1. The horizontal axes show the number of days until first preliminary estimate of official GDP releases.
2. The contribution of each dependent variable to forecasts is defined as difference between the forecast before the data reflects and after the data reflects. Therefore, it contains the effect of estimated coefficient changes.
3. Google Trends and METIPOS are reflected to forecasts after their monthly data become available.

Sources: Cabinet Office; Ministry of Economy, Trade and Industry; Bank of Japan; Japan Center for Economic Research "ESP Forecast Survey"; Google; Japan Automobile Dealers Association; Japan Mini Vehicle Association.

Data Description

Name	Frequency	Source	Trans-formation	Reporting lag (months)	Reporting lag (days)
Index of tertiary industry activity	Monthly	METI	mom change	2	42 - 51
Index of industrial production	Monthly	METI	mom change	1	26 - 31
Real exports	Monthly	BOJ	mom change	1	16 - 23
Real imports	Monthly	BOJ	mom change	1	16 - 23
Economy Watchers Survey (DI for current conditions, household activity-related)	Monthly	CAO	level	1	8 - 14
Real sales values of wholesale industry （Deflated by producer price index）	Monthly	METI （Deflator ： BOJ）	mom change	1	25 - 31
Survey of production forecast (Adjusted value)	Monthly	METI	mom change	0	-3 - 0
Number of new passenger car registrations	Monthly	JADA, JMVA	mom change	0	1 - 6
Google trends	Daily, converted to monthly	Google	mom change	0	1
METIPOS retail sales value index	Weekly, converted to monthly	METI	mom change	0	5 - 9
JCER ESP forecast (Forecast of GDP growth rate)	Monthly	JCER	qoq change	—	—
Official GDP estimate (The first preliminary)	Quarterly	CAO	qoq change	2	46 - 48

Notes: 1. Reporting lag indicates the approximate lag between month-end (or quarter-end) date and data release dates.
2. All data are seasonally adjusted (If the source does not publish seasonally adjusted series, the data are adjusted using X-12-ARIMA).