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Nowcasting gross domestic product in Japan using professional forecasters' information

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Abstract

This study proposes a new framework for nowcasting, the prediction of the present, the very near future, and the very recent past. Most previous research use a dynamic factor model (DFM) and insist that it is the best method for nowcasting. However, the DFM takes considerable time and effort and for Japanese GDP, the forecast result with DFM is not necessarily good (Bragoli, 2017).

We use professional forecasters' information instead.

In this study, we combine professional forecasters' information with single-equation approaches, such as bridge equations (BEQ) and mixed-data sampling (MIDAS) regressions. We use cross-sectional disagreement among forecasters in the ESP forecast survey, which is the first monthly survey of macroeconomic forecasts conducted by professional forecasters in Japan.

Key Words: Nowcasting; Forecast disagreement;

JEL Classification: C13; C32; E32; E37.

1 Introduction

Gross domestic product (GDP) is a key indicator for decision makers in governments, central banks, financial markets, and non-financial firms. However, GDP is available only on a quarterly basis, and is subject to substantial publication lags. In Japan, the first Quarterly Estimate (QE) of GDP is released approximately one and half months after the end of the reference quarter.

Thus, many prior studies propose several methods to nowcast GDP and find that the dynamic factor model (DFM) is the best method. For example, Jansen *et al.*.(2016) conduct a systematic comparison of the short-term

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forecasting abilities of twelve statistical models and find the DFM is the best model overall.

Bragoli (2017) is the latest study to use the DFM to nowcast GDP in Japan in its proposal of a formal statistical framework to monitor current economic conditions in Japan in real time. Using around 30 variables, they apply the DFM and compare the results with the AR1 model forecasts. However, their results are not necessarily good. In the fully real-time setting, their results do not differ from those of the AR1 model. Urasawa (2014) was the first to nowcast GDP in Japan using the DFM, finding that the forecast performance does not necessary improve when increasing the number of variables. Hara and Yamane (2013) find that the Index of Industrial Production (IIP) and the Index of Tertiary Industries Activity (ITA) can explain a large part of the variation in GDP growth.

On the other hand, Jansen *et al.*. (2016) find that forecasts by professional forecasters tend to perform better during periods of crisis. Legerstee and Franses (2015) examine the predictive power of disagreement among forecasters. As many prior studies insist, forecasters have asymmetric and different loss functions; they update their forecasts in different ways and particular information might cause disagreement among forecasters. Zarnowitz and Lambros (1987) show a positive correlation between disagreement among forecasters and uncertainty, which is a lack of confidence. Thus, we expect that disagreement among forecasters to increase, especially in a recessionary phase when forecast error increases.

In this study, we combine professional forecasters' information with single-equation approaches, such as bridge equations (BEQ) and mixed-data sampling (MIDAS) regressions. We use cross-sectional disagreement among forecasters in the ESP forecast (ESPF) survey, which is the first monthly survey of macroeconomic forecasts conducted by professional forecasters in Japan[1].

The remainder of the paper proceeds in three sections. Section 2 explains the data, base model, and its performance. Section 3 examines the combination of professional forecasters' information with base model. Section 4 provides the interpretation and conclusion.

2 Data and base model

2.1 Data set

Following Hara and Yamane (2013), we use IIP and ITA to build the base model for forecasting GDP growth. Although Hara and Yamane (2013) use historical data, we use real-time data to compare our results with those in

[1]ESP represents "Economy, Society, and Policy," published by the public relations magazine of the Cabinet Office, and does not stand for extrasensory perception(Komine *et al.*, 2009)

Bragoli (2017). We use the first QE as the actual to compare with the forecast.

We collect professional forecasters' information from the ESPF survey data set compiled by the Japan Center for Economic Research (JCER) [2]. The ESPF survey is the first monthly survey of macroeconomic forecasts conducted by professional forecasters in Japan. We can also obtain monthly forecasts for Japan through Consensus Economics, the world's leading international economic survey organization, which is older than the ESPF. However, in Japan, the ESPF panel has twice the number of participants as the Consensus Economics panel does.

Each month since April 2004, the ESPF survey polls professional forecasters from private economic institutions in Japan for their predictions about the main macroeconomic indicators. Neither the Bank of Japan (BOJ) nor the Japanese government participates in the survey. The ESPF requests respondents to provide annual and quarterly forecasts at the beginning of each month. Approximately 40 participants respond every month.

Our sample ranges from April 2004 to March 2017 and consists of 156 monthly observations. In our sample, we have 58 respondents, 25 of whom participated in 90 percent of the survey.

2.2 Base model

This section outlines our method of nowcasting the first QE. We suppose that nowcasting and backcasting are conducted at the top of the month because the ESPF requests respondents to provide annual and quarterly forecasts at that time.

We use the BEQ to nowcast GDP [3]. We estimate the quarterly relationship between GDP, the IIP, and the ITA using four kinds of regression:

$$\begin{aligned}
d\log(GDP_t) &= \alpha_1 + \beta_1 d\log(IIP_t) + \epsilon_{1t} &(1)\\
d\log(GDP_t) &= \alpha_2 + \beta_2 d\log(IIP_t) + \gamma_2 d\log(ITA_t) + \epsilon_{2t} &(2)\\
d\log(GDP_t) &= \alpha_3 + \beta_3 d\log(IIP_t) + \delta_3 d\log(GDP_{t-1}) + \epsilon_{3t} &(3)\\
d\log(GDP_t) &= \alpha_4 + \beta_4 d\log(IIP_t) + \gamma_4 d\log(ITA_t) \\
&\quad + \delta_4 d\log(GDP_{t-1}) + \epsilon_{4t} &(4)
\end{aligned}$$

We forecast monthly IIP and ITA if necessary using the ARIMA model.

Table 1 summarizes the timing of nowcasting and backcasting, as well as the information available.

In the first and second months of nowcasting, we have to make two-quarter ahead forecasts. The actual GDP one quarter before the reference

[2] The ESPF was conducted by the Association for Economic Planning since April 2004, and was taken over by the JCER from April 2012

[3] We also adopt a MIDAS regression; however, it provided worse results than the BEQ did.

Table 1: Information available for forecasting (example for Q3)

		GDP	IIP	ITA
Nowcast	Month1	Q1(2nd)	May	April
	Month2	Q1(2nd)	June	May
	Month3	Q2(1st)	July	June
Backcast	Month1	Q2(2nd)	August	July
	Month2	Q2(2nd)	September	August

Table 2: Base model estimation results

	(1)	(2)	(3)	(4)
C	0.00*	0.00*	0.00**	0.00**
IIP	0.23***	0.18***	0.24***	0.18***
ITA		0.47***		0.53***
rgdp(-1)			-0.13	-0.18**
Adj-R	0.75	0.81	0.76	0.83
AIC	-7.32	-7.54	-7.34	-7.67
SIC	-7.24	-7.42	-7.22	-7.50

Notes: Estimation period:2006Q1-2016Q4. The null hypothesis of the parameter equal to zero is rejected at the 10% (*), 5%(**), and 1% (***) significance levels.

quarter is not available. We also have to forecast monthly IIP and ITA 4 to 5 months ahead.

In the third month of nowcasting, we can obtain the actual GDP one quarter before the reference quarter. In the second month of nowcasting, we can obtain the actual IIP one quarter before the reference quarter, but we must make a one-month ahead forecast for ITA.

2.3 Base model results

Table 2 presents the estimation results for the real-time GDP forecast using the four base models.

The observation period is 2004Q4, the start of the chain-based first QE, to 2016Q4. We do a rolling estimation using 10 years (40 quarters) of real-time data. We estimated the results in Table 2 using data from 2006Q1 to 2016Q4. The adjusted R^2 of around 0.8 in Table 2 indicate that these models can explain a large part of the variation in GDP growth.

On the other hand, a lag in GDP improves the performance very little. This is in line with the performance of the AR1 model, which as an adjusted R^2 of around 0.

Table 3: Real-time GDP forecast results(1)

			Base Model				
		AR1	(1)	(2)	(3)	(4)	ESP
Evaluation period: 2004Q4 - 2016Q4							
Nowcast	Month1	1.17	1.59	1.77	1.59	1.80	0.80
	Month2	1.17	0.92	0.92	0.92	0.92	0.73*
	Month3	1.10	0.96	1.05	0.99	1.06	0.67*
Backcast	Month1	1.12	0.74*	0.80	0.75*	0.83	0.52**
	Month2	1.12	0.50**	0.50**	0.51**	0.53**	0.29***
Excluding: 2008Q2 - 2009Q1							
Nowcast	Month1	0.87	2.09	2.36	2.09	2.41	0.71
	Month2	0.87	1.15	1.16	1.16	1.16	0.71
	Month3	0.91	0.90	0.94	0.94	0.96	0.64
Backcast	Month1	0.92	0.67	0.65	0.68	0.69	0.54*
	Month2	0.92	0.50**	0.46**	0.51**	0.50**	0.36**

Notes: For AR1, the entries refer to the RMSE; for all other models, they refer to the RMSE relative to the AR1 model's RMSE. The null hypothesis of no difference is rejected at the 10% (*), 5%(**), and 1% (***) significance levels.

Table 3 shows the result of the real-time GDP forecast with an evaluation period from 2004Q4 to 2016Q4. Of all the nowcasts and backcasts, the ESPF provides the best forecast. All relative Root Mean Squared Error (RMSE) values compared to the AR1 model's RMSE are below one. Using the Diebold and Mariano (2002) test of equal predictive accuracy, the forecasting performance between the AR1 model and ESPF is significant, except in the first month's nowcast.

Excluding 2008Q2 to 2009Q1, when the economic downturn occurred after the financial crises, the ESPF performs significantly better only for the backcast. This is in line with Jansen's *et al.*. (2016) finding that professional forecasters tend to perform better during periods of crisis.

Among the four models, those without the lag of GDP, models (1) and (2), tend to perform better. Although the adjusted R^2 of model (2) is better than that for model (1), these two models have similar performance because we must forecast monthly ITA, even in the second month's backcast. Hereafter, we use the real-time forecast result for model (2) because it contains more information. Using the Diebold and Mariano (2002) test of equal predictive accuracy, the forecasting performance difference between the real-time forecast results of model (2) and ESPF is not significant.

3 Combination of professional forecasters' information with the base model

3.1 Forecast averaging

In this section, we examine two methods to combine professional forecasters' information with model forecasting: forecast averaging and a single-equation approach with professional forecasters' information.

Most prior studies show that forecast averaging improves performance. There is room to improve the performance if we average the real-time forecast results of model (2) and the ESPF because the difference between the two is not significant.

Following Stock and Watson (2001), we use the weight w calculated by equation (5) to average the real-time forecast result of model (2) and the ESPF. $w \times ESPF + (1-w) \times model(2) forecast$ is the averaged forecast.

$$w = \frac{1/ABSFE_{espf}}{1/ABSFE_{espf} + 1/ABSFE_{model}}, \tag{5}$$

where $ABSFE_{espf}$ is the absolute forecast error of the ESPF and $ABSFE_{model}$ is the absolute forecast error of the real-time forecast result of model(2). Figure 1 shows the ex-ante variation of w in the second month backcast. Figure 2 shows the trend in disagreement among professional forecasters. The shaded areas indicate recessionary phases determined by the Japanese government. Disagreement becomes larger, especially from 2008Q2 to 2009Q1, when the economic downturn occurred after the financial crises. Disagreement also increased in 2011Q2 immediately after the Great East Japan Earthquake and in 2014Q2 when the consumption tax rate was raised from 5 percent to 8 percent.

We have to forecast w because we cannot know the ABSFE before the actual data are released. Stock and Watson (2001) propose using the past mean squared error of each forecast instead the ABSFE in equation (5). Here, we propose forecasting w using the disagreement between forecasters in the ESPF. We use the root mean squared deviation among individual forecasts as a measure of forecast disagreement. As many prior studies show, disagreement increases when uncertainty in the Japanese economy also increases.

Table 4 shows the estimation results. In the backcast, the parameter of disagreement is positive and significant. This means that the weight for ESPF increases as disagreement increases. The disagreement tends to become larger when the economy is in a recession phase. This is in line with Jansen's *et al.*(2016) finding that forecasts by professional forecasters tend to perform better during periods of crisis.

Figure 1: Ex-ante variation of w in the second month backcast

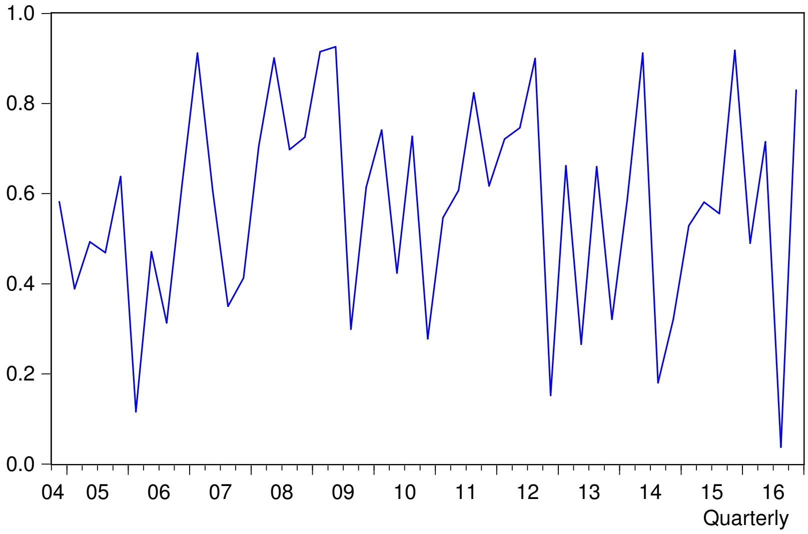

Figure 2: Trend in disagreement among professional forecasters

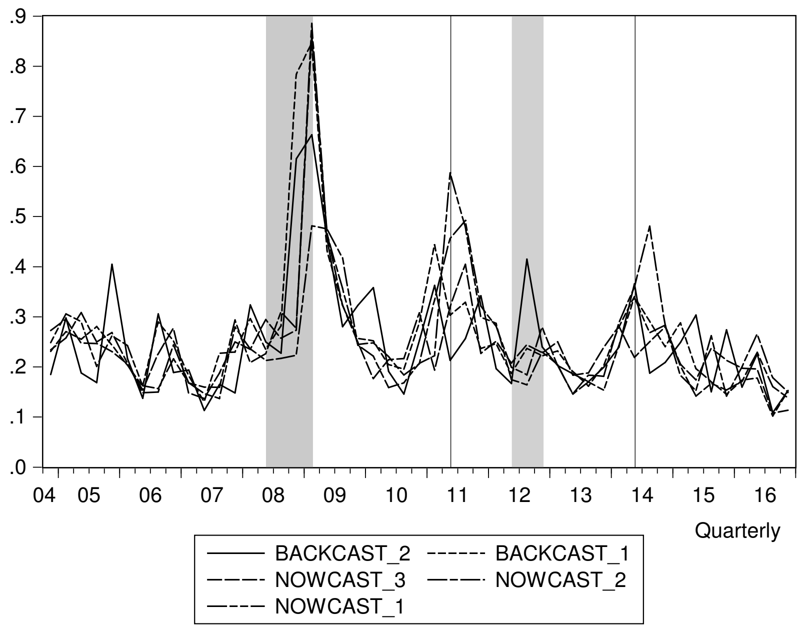

Table 4: Forecast combination estimation results (1)

		C	Disag	Adj-R	AIC	SIC
Nowcast	Month1	0.45***	0.30	0.00	-0.29	-0.21
	Month2	0.59***	-0.24	0.00	-0.04	0.04
	Month3	0.40***	0.40	0.02	-0.20	-0.13
Backcast	Month1	0.43***	0.26*	0.00	-0.01	0.07
	Month2	0.37***	0.82***	0.14	-0.20	-0.12

Notes: Estimation period: 2004Q4-2016Q4. The null hypothesis of the parameter equal to zero is rejected at the 10% (*), 5%(**), and 1% (***) significance levels.

Table 5: Forecast combination estimation results (2)

		C	ModelF	Disag	Adj-R	AIC	SIC
Nowcast	Month1	0.49	0.00	-1.32	-0.03	3.04	3.15
	Month2	0.67**	0.34**	-1.94	0.24	2.74	2.85
	Month3	0.02	0.46***	0.22	0.42	2.48	2.59
Backcast	Month1	0.74**	0.44***	-2.41*	0.64	1.98	2.10
	Month2	0.44*	0.70***	-1.43	0.79	1.47	1.58

Notes: Estimation period: 2004Q4-2016Q4. The null hypothesis of the parameter equal to zero is rejected at the 10% (*), 5%(**), and 1% (***) significance levels.

3.2 Single-equation approach with professional forecasters' information

The second approach is to estimate equation (6) to forecast GDP growth.

$$dlog(GDP_t) = \alpha_5 + \beta_5 model(2)forecast_t + \gamma_5 disagreement_t + \epsilon_t \qquad (6)$$

Disagreement tends to increase, and forecasts using a single-equation approach tend to be optimistic when the economy is in a contraction. We expect a negative value for the parameter γ_5. Table 5 reports the estimation results. Although most of the γ_5 values are negative, is significant only in the first month's backcast. In the first month backcast, we have to forecast the one-month ahead IIP and two-month ahead ITA, so there is room to improve forecast performance using disagreement.

3.3 Forecast comparisons

Using the estimation results, we create two types of combination forecasts and report the results in Table 6. Combi(1) refers to the forecast average and combi(2) refers to the Single-equation approach with professional forecasters' information. We use the Mean Absolute Forecast Error (MAE) and Mean Absolute Forecast Percentage Error (MAPE) besides the RMSE to evaluate the forecasts.

If we evaluate the full sample (2004Q4-2016Q4), the ESPF offers the best performance in most cases. However, excluding 2008Q2 to 2009Q1, when the economic downturn occurred, Combi(1) performs better than the ESPF in the backcast. This means that averaging the ESPF and model forecasts improve forecast performance under normal economic circumstances. On the other hand, the Combi(2) model has notably better than Model(2) does in nowcasting; thus, it is possible to improve the performance of the single-equation forecast using disagreement among forecasters.

4 Interpretation and conclusion

In this paper, we propose a new framework for nowcasting. We examine two types of combinations of professional forecasters' information with model forecasting: forecast averaging and a single-equation approach with professional forecasters' information. In the backcast, averaging the ESPF and single-equation approach forecast using the weight estimated by disagreement among forecasters can improve performance. In the nowcast, disagreement among forecasters improves the performance of single-equation forecasts.

As Legerstee and Franses (2015) state, forecast disagreement is useful for forecasting because it becomes larger during recessions. In addition,

Table 6: Real-time GDP forecast results (2)

		RMSE	MAE	MAPE
Nowcast Month1	ESP	**0.936**	**0.626**	116.546
	Model(2)	2.069	0.877	130.741
	Combi(1)	1.244	0.695	106.506
	Combi(2)	0.968	0.684	**104.830**
Nowcast Month2	ESP	0.855	**0.592**	**110.399**
	Model(2)	1.080	0.676	131.003
	Combi(1)	0.858	0.598	115.572
	Combi(2)	**0.832**	0.616	117.526
Nowcast Month3	ESP	**0.733**	0.540	106.557
	Model(2)	1.154	0.693	127.117
	Combi(1)	0.752	**0.534**	107.425
	Combi(2)	0.796	0.555	**94.139**
Backcast Month1	ESP	**0.577**	0.447	**87.507**
	Model(2)	0.894	0.544	114.606
	Combi(1)	0.580	**0.441**	96.726
	Combi(2)	0.618	0.480	113.857
Backcast Month2	ESP	0.323	**0.257**	**66.435**
	Model(2)	0.561	0.400	83.710
	Combi(1)	**0.322**	0.270	67.197
	Combi(2)	0.474	0.382	92.266

Notes: Evaluation period: 2004Q4-2016Q4. Figures in bold indicate the best model among all models.

Table 7: Real-time GDP forecast results(3)

		RMSE	MAE	MAPE
Nowcast Month1	ESP	**0.615**	**0.497**	112.598
	Model(2)	2.047	0.790	129.728
	Combi(1)	1.071	0.580	102.419
	Combi(2)	0.711	0.573	**100.747**
Nowcast Month2	ESP	**0.612**	**0.486**	**106.801**
	Model(2)	1.004	0.634	133.724
	Combi(1)	0.724	0.534	114.863
	Combi(2)	0.692	0.540	114.058
Nowcast Month3	ESP	**0.582**	**0.470**	102.812
	Model(2)	0.857	0.564	122.654
	Combi(1)	0.641	0.482	103.823
	Combi(2)	0.667	0.509	**90.870**
Backcast Month1	ESP	0.497	0.406	**84.591**
	Model(2)	0.597	0.436	116.164
	Combi(1)	**0.488**	**0.392**	95.469
	Combi(2)	0.556	0.444	112.874
Backcast Month2	ESP	0.330	**0.263**	69.486
	Model(2)	0.421	0.339	81.862
	Combi(1)	**0.317**	**0.263**	**68.034**
	Combi(2)	0.413	0.343	89.680

Notes: Evaluation period: 2004Q4-2016Q4, excluding 2008Q2-2009Q1. Figures in bold indicate the best model among all models.

the method outperforms Bragoli's (2017) DFM. Nowcasting with single-equation forecasts using forecasters' information is practical because it is easy to implement.

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