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Time varying biases and the state of the economy

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ABSTRACT

This paper aims to investigate whether a forecast is optimal, given the information available when it is made. Going beyond the papers that study forecast errors based on the model of Nordhaus (1987), we use a time-varying procedure to forecast revisions and to account for the possibility that the duration of the state may also affect the bias. Three testable hypotheses are presented to help researchers test the optimality of forecasts, with the ultimate aim of determining whether these biases depend on the underlying economic state and whether they are persistent for the duration of the state. Corresponding bias-corrected forecasts can then be made based on these results. The empirical study finds that the one-quarter-ahead official forecast of GDP growth in Taiwan does indeed suffer from state-dependent biases: a persistent under-estimation bias in the relatively good state, and an under-reaction bias that decays with duration in the relatively bad one. Eliminating these biases in the forecast can remove over 44.0% of the variation in forecast errors, and pseudo out-of-sample experiments further support the fact that the resulting bias-corrected forecasts are markedly better than those made by Taiwan's government or using other competing models.

1. Introduction

Given the available information, conventional theory suggests that the optimal forecast, in the sense of minimized expected mean squared forecast errors (MSFE), must be the "rational expectation" of the target variable. The optimal forecast is unbiased because the induced forecast error has a zero mean, and efficient because the error is unpredictable and orthogonal to the components of the given information set when the forecast is made.

There are two conventional types of regression models proposed in the literature for investigating whether a forecast is optimal. One focuses on the relationship between realized and forecasted values directly (e.g., Mincer & Zarnowitz, 1969), while the other turns to the properties of the forecast errors (e.g., Holden & Peel, 1990 and Nordhaus, 1987). Note that the parameters of these two types of models are assumed (implicitly) to be constant over time, and thus the implied bias (non-zero mean of the forecast error) of a forecast is time-invariant; see e.g. Artis and Marcellino (2001), Gavin and Mandal (2003), Holden and Peel (1990), Loungani (2001), Mincer and Zarnowitz (1969), and Nordhaus (1987).

However, many studies analyzing survey data have shown that the forecast performance can be correlated strongly with the underlying economic conditions; see for example Chauvet and Guo (2003), Döpke (2001), Fildes and Stekler (2002), Grunberg and Modigliani (1954), Messina, Sinclair, and Stekler (2015), Sinclair, Joutz, and Stekler

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(2010), Sinclair, Stekler, and Carnow (2015), and Swanson and van Dijk (2006). This empirical evidence reveals that the bias of a forecast could be time-varying, and may depend on the underlying economic state and its duration.

To explain the possible time-varying bias of a forecast, Messina et al. (2015) and Sinclair et al. (2010, 2015) modify the models of Holden and Peel (1990), Mincer and Zarnowitz (1969), and Nordhaus (1987) by introducing a state variable whose values are identified for the corresponding target periods *ex post*. In essence, they aim to investigate whether the forecasts incorporate the knowledge of the "future state" of the economy that was available at the time when the forecast was made. Therefore, their models cannot be used to infer whether the forecast is actually optimal. Moreover, they neglect the possibility that the duration of the state may also help to explain the forecast error.

Going beyond the studies mentioned above, this paper proposes a new framework for investigating whether the forecast is optimal by extending the regression model of Nordhaus (1987). Since the proposed model accounts for the possibility that the underlying economic state and its duration may also affect the bias, we demonstrate how these time-varying biases of a forecast can be detected given the information set available at the time when the forecast is made. The innovative features of the proposed model, which cannot be found in previous works considering a series of published forecasts, are that it can help researchers to (1) test the conventional rationality of a forecast; (2) ascertain whether the existing biases depend on the underlying state of the economy when the forecast was made; (3) determine whether these biases remain persistent even when the duration of that economic state lengthens; and (4) construct a feasible bias-corrected forecast with a lower MSFE once the forecast has been published (which is useful for the real-time analysis in particular).

The framework proposed here is used to analyze the real GDP growth (one-quarter-ahead) forecast from the Taiwan government. The analysis is based on 105 real-time data vintages in Taiwan, and shows that this forecast suffers from time-varying biases that depend on the underlying economic state and its duration. Specifically, the Taiwan government tends to under-estimate GDP growth in relatively good states, and this bias is persistent. On the other hand, in relatively bad economic states, the government under-reacts to the received news; however, this bias disappears as the time in the state lengthens. Moreover, neither the official forecast nor other forecasts made using competing models substantially outperform the proposed bias-corrected forecast in pseudo out-of-sample experiments with Taiwan's GDP growth forecasts.

The rest of this paper is organized as follows. Section 2 introduces the methodology. Section 3 presents a relevant empirical study of forecast in Taiwan, and Section 4 draws conclusions.

2. Methodology

2.1. Optimal forecast and testable models

Let y_t be the realized GDP growth rate at time t, and $y^f_{t|t-h}$ be its h-step-ahead forecast published at time $t-h$ for $h > 0$. Accordingly, define the (one-step-ahead) forecast error as $e_t \equiv y^f_{t|t-1} - y_t$, where $e_t > 0$ indicates an over-prediction and $e_t < 0$ indicates an under-prediction.

Let Ω_t denote the information set available at time t; then, conventional forecasting theory claims that the optimal one-step-ahead forecast should be $\mathbb{E}[y_t|\Omega_{t-1}]$, the conditional expectation of y_t given the information set at time $t-1$, while minimizing the expected MSFE (see Patton & Timmermann, 2012, for example). It immediately follows that, if $y^f_{t|t-1}$ is optimal, the resulting forecast error e_t should satisfy the moment condition as

$$\mathbb{E}[e_t|\Omega_{t-1}] = 0, \tag{1}$$

which also implies that e_t should have zero mean (meaning that $y^f_{t|t-1}$ is unbiased) and be orthogonal to the variables in Ω_{t-1} (meaning that $y^f_{t|t-1}$ is efficient).

Holden and Peel (1990) propose the following simple regression to test for the unbiasedness of a forecast:

$$e_t = \mu + u_t, \tag{2}$$

where u_t is the zero-mean unpredictable disturbance at time $t-1$. Given this model, $\mu = 0$ implies that the forecast is unbiased, while a non-zero μ implies a biased forecast.[1] On the other hand, in an attempt to introduce some of the variables available in Ω_{t-1} into a test for the unbiasedness and efficiency of $y^f_{t|t-1}$, Nordhaus (1987) considers the model for the forecast error as

$$e_t = \alpha + \beta \cdot FR_{t-1} + u_t, \tag{3}$$

where the variable $FR_{t-1} \equiv y^f_{t|t-1} - y^f_{t|t-2}$ is known as the forecast revision, and measures the forecaster's adjustment of the forecast in response to the new information received between times $t-2$ and $t-1$.[2] The intercept α indicates the possibly systematic estimation error of the forecasts, and the slope β measures how all of the new information is incorporated into the forecast made at time $t-1$; thus, $\beta > 0$ ($\beta < 0$) reflects the forecaster's over-reaction (under-reaction) to the information received.[3] Thus, throughout this paper, we interpret positive values of α as an over-estimation bias and negative ones as an under-estimation bias, while a positive (negative) β indicates an over-reaction (under-reaction) bias. If the forecast is optimal, then the null that $\alpha = \beta = 0$ should not be rejected significantly by the observed data. In addition, from a model selection perspective, if the estimate of β is significantly non-zero, the model of Holden and Peel (1990) in Eq. (2) may not be appropriate for modeling e_t, since the variable FR_{t-1} can help to explain e_t statistically.

[1] Note, however, that an unbiased forecast does not necessarily imply that the forecast is efficient if the residual of the regression in Eq. (2) is serially correlated; see Gavin and Mandal (2003) and Joutz and Stekler (2000).

[2] For example, a positive revision occurs when the forecaster receives some good news about the economy. If the forecaster expects the news to have a larger impact on the economy, then there will be a larger revision to the forecast.

[3] In the literature, the intercept $\alpha > 0$ ($\alpha < 0$) can be interpreted as the behavioral bias of optimism (pessimism), while $\beta > 0$ ($\beta < 0$) captures the behavioral bias of over-reaction (under-reaction) to new information; see e.g. Amir and Ganzach (1998), Ashiya (2003), and Ehrbeck and Waldmann (1996). In particular, Ehrbeck and Waldmann (1996) establish a structural model, and Amir and Ganzach (1998) propose a theory to support these existing behavioral biases.

2.2. Time varying biases and the state of the economy

Since many of the studies analyzing survey data have shown that the forecast performance can be correlated strongly with the underlying economic conditions,[4] we go on to consider time-varying biases in different states of the economy by modifying Nordhaus' model in Eq. (3) above as

$$e_t = [\alpha_0 + \beta_0 \cdot FR_{t-1}] \times (1 - \hat{s}_{t-1}) + [\alpha_1 + \beta_1 \cdot FR_{t-1}] \times \hat{s}_{t-1} + u_t, \tag{4}$$

where $\hat{s}_{t-1}$ is the available estimate (or proxy) of the underlying state of the economy at time $t-1$, given the information set Ω_{t-1}. Throughout this paper, $\hat{s}_{t-1} = 0$ stands for a relatively bad state and $\hat{s}_{t-1} = 1$ for a relatively good one. Based on this setting, we can capture the possible time-varying biases-state-dependent over-estimation/under-estimation biases and over-reaction/under-reaction biases. In practice, we would prefer to use this model with time-varying biases rather than Nordhaus' model in Eq. (3) if the data statistically reject the null that $\alpha_0 = \alpha_1$ or/and the null that $\beta_0 = \beta_1$.

2.2.1. Proxy for the state variable

When the relatively bad and good states of the underlying economic conditions are of interest, a feasible proxy variable for $\hat{s}_{t-1}$ at time $t-1$ can be constructed as per Ang, Bekaert, and Wei (2007), given the information set Ω_{t-1}. This implementable proxy is modeled using deviations from a D-quarter moving average (MA):

D-quarter MA:

$$\hat{s}_{t-1} = \begin{cases} 0, & \text{if } y_{t-1} - \dfrac{1}{D}\displaystyle\sum_{i=1}^{D} y_{t-1-i} \le 0, \\ 1, & \text{otherwise.} \end{cases} \tag{5}$$

The estimated underlying state of the economy at time $t-1$ is identified as a relatively bad state if y_{t-1} does not exceed its previous D-quarter moving average (y_{t-1} is decelerating); otherwise, the economy would be regarded as being a relatively good state at time $t-1$ (y_{t-1} is accelerating).

There are several remarks that should be made about this proxy. Firstly, the values of this proxy for the state of the underlying economy are not exactly equal to the ones identified *ex post* by the relevant government institute, such as National Bureau of Economic Research (NBER) in the United States. The exact business cycle dates are not of interest here because they cannot be used to test the optimality of the forecast, since they are not observed at the time when the forecast is made. This proxy in Eq. (5) tries to capture the relative momentum of the underlying economy based on the feasible information set instead. Secondly, in most cases, the finalized value of y_{t-1} is also unobserved at time $t-1$ when the forecast for y_t is made. However, some initial, preliminary or estimated values for y_{t-1} ($\hat{y}_{t-1}$, say) based on Ω_{t-1} can be obtained, and thus, this MA proxy $\hat{s}_{t-1}$ can still be computed when the value of y_{t-1} is replaced with $\hat{y}_{t-1}$ in Eq. (5). Finally, an alternative proxy variable for the state of the economy may also be obtained using approaches such as the band-pass filter proposed by Christiano and Fitzgerald (2003) or the business cycle dating algorithm developed by Bry and Boschan (1971) and Harding and Pagan (2001), or can be derived from the well-known Markov-switching models or state space framework in the literature. However, the estimation problems thus induced are sometimes tedious.

2.3. The proposed model

In addition to the relative state of the economy at time $t-1$, the length of time it has been in this state to time $t-1$ may also affect the forecast released, such that the potential biases are time-varying. Let $\hat{d}^0_{t-1}$ and $\hat{d}^1_{t-1}$ denote the durations of the relatively bad and relatively good states, respectively, until time $t-1$, given $\hat{s}_{t-1}$[5]; then, we propose a general model to test the moment condition in Eq. (1) as

$$\begin{aligned} e_t = {} & \left[\alpha_0 \exp\left(-\gamma^0_\alpha \cdot \hat{d}^0_{t-1}\right) + \beta_0 \exp\left(-\gamma^0_\beta \cdot \hat{d}^0_{t-1}\right) FR_{t-1}\right] \times \left(1 - \hat{s}_{t-1}\right) \\ & + \left[\alpha_1 \exp\left(-\gamma^1_\alpha \cdot \hat{d}^1_{t-1}\right) + \beta_1 \exp\left(-\gamma^1_\beta \cdot \hat{d}^1_{t-1}\right) FR_{t-1}\right] \times \hat{s}_{t-1} + u_t, \end{aligned} \tag{6}$$

where $\gamma^0_\alpha, \gamma^0_\beta, \gamma^1_\alpha$ and γ^1_β are non-negative state-dependent parameters, with the superscript "0" standing for the relatively bad state and "1" for the relatively good one.

Several remarks should be made about this model. Firstly, for $i = 0, 1$ and $j = \alpha, \beta$, if the parameter γ^i_j is greater than zero, the function $\exp(-\gamma^i_j \cdot \hat{d}^i_{t-1})$ in Eq. (6) is only the well-known exponential survivor function; thus, γ^i_j can then be interpreted as the probability that the forecaster will cease to suffer from the corresponding bias, and the expected duration is known to be $(\gamma^i_j)^{-1}$.[6] This implication is of interest because it helps in determining how long these forecast biases would take to die out on average. Secondly, if $\gamma^i_j = 0$, it can be interpreted as the situation where the forecaster is not very aware of the ongoing economy, even though the underlying state is of a longer duration; thus, this induced bias is persistent.

[4] See for example Ashiya (2007), Chauvet and Guo (2003), Döpke (2001), Fildes and Stekler (2002), Gavin and Mandal (2003), Granger (1996), Grunberg and Modigliani (1954), Loungani (2001), Swanson and van Dijk (2006), and Zarnowitz (1992).

[5] Consider for example the case $\hat{d}^0_{t-1} = 3$, which means that $\hat{s}_{t-1} = \hat{s}_{t-2} = \hat{s}_{t-3} = 0$, and $\hat{s}_{t-4} = 1$, so the economy has stayed in the relative bad state for three periods, from $t-3$ to $t-1$. Likewise, $\hat{d}^0_{t-1} = 1$ means that the state at time $t-1$ (relatively bad state) differs from that at time $t-2$ (relatively good state).

[6] It is also possible to consider other survivor functions, such as Weibull or log–logistic functions. However, as these survivor functions are more general than the exponential one because they introduce more parameters, it turns out that we may not be able to obtain the convergent estimates of those general survivor functions easily in practice, especially when the sample period is not long enough. For more properties and a further discussion of survivor functions, see Kiefer (1988), for example.

Moreover, the proposed model in Eq. (6) degenerates to the model in Eq. (4) if all of $\gamma_j^i,\ i = 0, 1,\ j = \alpha, \beta$, are equal to zero; thus, empirically, we can determine which of these models to select by testing whether the estimates of γ_j^i in the data are significantly non-zero.

2.4. Inferences and implications

2.4.1. Three testable hypotheses concerning forecast error

Given the proposed model in Eq. (6), determining its value requires the validity (or otherwise) of the conventional theory of optimal forecasts to be determined first.

Hypothesis 2.1 (*Optimal Forecast*)**.** If the forecast is optimal for minimizing the mean squared forecast error given the information set at the time when the forecast is made, then $\alpha_0 = \beta_0 = \alpha_1 = \beta_1 = 0$.

In addition to considering four individual tests based on the corresponding estimates of these four parameters, our empirical study also considers three implied null hypotheses, namely

$$H_o : \alpha_0 = \alpha_1 = 0;$$
$$H_o : \beta_0 = \beta_1 = 0;$$
$$H_o : \alpha_0 = \beta_0 = \alpha_1 = \beta_1 = 0.$$

Rejecting any of these suggests that either the forecast is non-optimal or the minimum MSFE is not the forecaster's only concern.

Going beyond the model of Nordhaus (1987), the proposed model also emphasizes the time-varying biases, because of the important role of the relative state of the underlying economy in forming forecast errors. It is therefore of interest to determine whether or not the induced biases are independent of the underlying economic state when the forecast is made. To this end, the following hypothesis may be tested:

Hypothesis 2.2 (*State-Independent Bias*)**.** If all of the potential biases are independent of the state of the economy, then $\alpha_0 = \alpha_1$, $\beta_0 = \beta_1$, $\gamma_\alpha^0 = \gamma_\alpha^1$ and $\gamma_\beta^0 = \gamma_\beta^1$.

Three implied joint tests are of particular interest:

$$H_o : \alpha_0 = \alpha_1, \qquad \gamma_\alpha^0 = \gamma_\alpha^1;$$
$$H_o : \beta_0 = \beta_1, \qquad \gamma_\beta^0 = \gamma_\beta^1;$$
$$H_o : \alpha_0 = \alpha_1, \qquad \gamma_\alpha^0 = \gamma_\alpha^1, \qquad \beta_0 = \beta_1, \qquad \gamma_\beta^0 = \gamma_\beta^1.$$

Rejecting the first hypothesis implies that the over-estimation and/or under-estimation biases are state-dependent; likewise, rejecting the second one indicates state-dependent over-reaction and/or under-reaction biases. The third test is a joint test of the first two; rejecting it means that some or all of these biases are state-dependent. In addition, rejections of any of these tests show that the data do not support the employment of Nordhaus' (1987) model for analyzing the forecast error.

Furthermore, if the induced biases do not disappear with the duration of the state, they are persistent. This may be due to the forecaster not being very aware of the ongoing economy, even though the duration of the underlying state is longer. Accordingly, if a bias is present in the forecast, we can determine whether this bias is persistent or not by testing the following hypothesis.

Hypothesis 2.3 (*Persistent Bias*)**.**

(i) If the bias caused by over-estimation or under-estimation of the forecast is persistent in a relatively bad (good) state of the economy, then $\gamma_\alpha^0 = 0$ ($\gamma_\alpha^1 = 0$).

(ii) If the bias caused by over-reaction or under-reaction to news is persistent in a relatively bad (good) state of the economy, then $\gamma_\beta^0 = 0$ ($\gamma_\beta^1 = 0$).

A few points should be made regarding Hypothesis 2.3. First, the persistent bias in the relative state of the underlying economy can also be viewed as a kind of systematic bias, as documented by Fildes and Stekler (2002). Second, the proposed Hypothesis 2.3 differs somewhat from the recent work of Coibion and Gorodnichenko (2012, CG hereafter). In CG's model, even rational forecasters may produce forecast errors, owing to limitations of information. This information rigidity will be lessened as the underlying state lasts for longer. Thus, they argue that "forecast errors converge back to zero over time, as agent's information sets progressively incorporate the new information". On the other hand, violations of Hypothesis 2.3 say that the forecast errors will converge back to zero over time as the biases disappear with the duration of the state, provided that the forecast is non-optimal; that is, the forecast biases still exist for finite lengths of the duration, which violates the idea of an optimal forecast.

2.4.2. Bias-corrected forecast

Recall that the main aim of this paper is to determine whether the one-step-ahead forecast $y^f_{t|t-1}$ is optimal given the information set Ω_{t-1} at time $t-1$. Thus, we propose the use of the model in Eq. (6), induced by the moment condition in Eq. (1), for detecting possible time-varying and state-dependent biases. Once the relevant parameters of this model for the forecast error can be estimated consistently, an interesting by-product at time $t-1$ is the so-called bias-corrected forecast, say, $y^{bc}_{t|t-1}$. It can be written as

$$y^{bc}_{t|t-1} = y^f_{t|t-1} - \hat{e}_t, \tag{7}$$

where $\hat{e}_t$ is an estimate of e_t based on Eq. (6), given the information set Ω_{t-1}. Notably, even though e_t ($= y^f_{t|t-1} - y_t$) is determined *ex post*, the bias-corrected forecast $y^{bc}_{t|t-1}$ at time $t-1$ can still be obtained readily, because all of the explanatory variables in Eq. (6) are observable when the one-step-ahead forecast $y^f_{t|t-1}$ is published by the forecaster. This property is particularly useful in the real-time analysis, because once the forecast has been published, we can obtain the corresponding bias-corrected version of a forecast immediately. The predictability of the bias-corrected forecast $y^{bc}_{t|t-1}$ cannot be worse than $y^f_{t|t-1}$ if the accuracy of a forecast is measured as the proportion of the volatility in the realization that the forecast accounts for correctly. Accordingly, the following always holds:

$$1-\frac{\text{var}\left(y_t-y^{bc}_{t|t-1}\right)}{\text{var}\left(y_t\right)}\geq 1-\frac{\text{var}\left(y_t-y^{f}_{t|t-1}\right)}{\text{var}\left(y_t\right)}, \quad (8)$$

since $y_t = y^f_{t|t-1} - e_t = (y^f_{t|t-1} - \hat{e}_t) - (e_t - \hat{e}_t) = y^{bc}_{t|t-1} - (e_t - \hat{e}_t)$.

2.5. Remarks

When comparing the framework above and the proposed model with the existing related works in the literature, there are various comments that should be made.

In addition to testing the optimality of $y^f_{t|t-1}$ via the moment condition of the forecast error in Eq. (1), we may also compare $y^f_{t|t-1}$ with the optimal forecast $\mathbb{E}[y_t|\Omega_{t-1}]$ directly. If $y^f_{t|t-1}$ is optimal given Ω_{t-1}, then we would expect $(\lambda, \delta) = (0, 1)$ in the following regression model:

$$y_t = \lambda + \delta y^f_{t|t-1} + u_t.$$

This is known as the model of Mincer and Zarnowitz (1969, MZ hereafter), and is also popular in the literature. Section 3.3.1 will provide an empirical comparison of the performances of this model and some of its variants with that of the proposed model.

For detecting the time varying biases, Messina et al. (2015) and Sinclair et al. (2010, 2015) also modify the Holden–Peel, MZ, and Nordhaus' models as follows:

$$e_t = \mu_0 \times (1 - s_t) + \mu_1 \times s_t + u_t,$$
$$y_t = \lambda_0 \times (1 - s_t) + \lambda_1 \times s_t + \delta y^f_{t|t-1} + u_t,$$
$$e_t = [\alpha_0 + \beta_0 \cdot FR_{t-1}] \times (1 - s_t) + [\alpha_1 + \beta_1 \cdot FR_{t-1}] \times s_t + u_t,$$

where the dummy variable s_t reflects the state of the economy at time t. In essence, they investigate whether the forecasts incorporate knowledge about the "future state" of the economy that is available at the time when the forecast is made. However, this paper tests the moment condition in Eq. (1) by introducing $\hat{s}_{t-1}$ to Eq. (4), and thus Eq. (6), to determine whether the forecast is optimal. Therefore, the spirit of these models is different to that proposed here. Besides, the values of their state variable s_t are identified *ex post*, and are infeasible at the time when the forecast is made; for example, Messina et al. (2015) determine the values of s_t based on NBER-dated recessions.

3. Empirical study of forecasts in Taiwan

3.1. Data description and a proxy for the state variable

This section conducts an empirical study of forecasts in Taiwan based on the proposed framework. The target of interest is the quarterly real output growth rate of Taiwan. The GDP growth forecasts and realized values from 1986Q4 to 2012Q3 are taken sequentially from *Quarterly National Economic Trends*, which is published routinely every February, May, August and November by the Directorate General of Budget, Accounting and Statistics (DGBAS) in Taiwan; there are 105 real-time data vintages. Based on the identification of the multiple-quarter-ahead forecast by Chang, Franses, and McAleer (2011), at the time when the one-quarter-ahead forecast is published, the DGBAS has known roughly the last realized quarterly GDP; the realized data used here are released approximately six to seven weeks after the quarter to which they refer.[7] This feature of the Taiwan data makes it possible to construct a proxy for the state variable $\hat{s}_{t-1}$ by using the realized y_{t-1} directly without estimating y_{t-1} in advance; cf. Eq. (5).

Fig. 1 plots the time series data. Panel (a) plots the realized GDP growth rate $\{y_t\}$ and its one-quarter-ahead forecast $\{y^f_{t|t-1}\}$, while panel (b) plots its corresponding forecast error $\{e_t\}$, and the shaded area represents the periods of a relatively bad state for which the proxy is constructed based on deviations from a four-quarter moving average, i.e., $D = 4$ in Eq. (5).

Fig. 1(a) suggests that the Taiwan government seems unable to adjust its prediction immediately in response to the news, since the forecast generally lags the realized Taiwan GDP growth rate, especially during volatile periods. Fig. 1(b) demonstrates that the DGBAS forecast error is likely to be correlated with the state of the economy. That is, the DGBAS tends to over-predict the GDP growth rate when GDP is decelerating, and to under-predict it when it is accelerating. Moreover, the magnitude of the DGBAS forecast error is also observed to vary with the duration of the state; in most cases, the absolute error initially increases and then decreases.

3.2. Results of conventional unbiasedness and efficiency analyses

We test whether the Taiwan forecasts are optimal or not by first employing some conventional models that have been proposed in the literature: the Holden–Peel regression model can be used to test for unbiasedness, while both the MZ and Nordhaus regressions are considered for testing the optimality of a forecast.

Table 1 reports the estimation results. The results for a typical Holden–Peel regression, i.e., $\hat{\mu}$ in model (a1), show that the forecast is biased, and the Ljung–Box Q-statistics indicate that the residuals of the regression are significantly autocorrelated. This implies that the forecast is inefficient, since the forecast error can be predicted from its past values. Meanwhile, both the conventional

[7] According to the definition used by Chang et al. (2011), if the target is the GDP growth in some quarter, the DGBAS's corresponding one-quarter-ahead forecast is identified as the forecast published in the second month of that quarter. For example, in February (the middle of Q1), the published forecast for Q1 is recorded as the "one-quarter-ahead" forecast for the Q1 GDP growth rate; likewise, the forecasts for Q2, Q3, and Q4 announced in Q1 are identified as the two-, three-, and four-quarter-ahead forecasts, respectively; see Chang et al. (2011, pp. 1070) for details. Incidentally, at the same time as the one-quarter-ahead forecast for Q1 GDP growth is released (in February), DGBAS also publishes the initial realized GDP growth from Q4 of the previous year. That is why we say that the DGBAS knew roughly the past realized GDP when the one-step-ahead forecast was published.

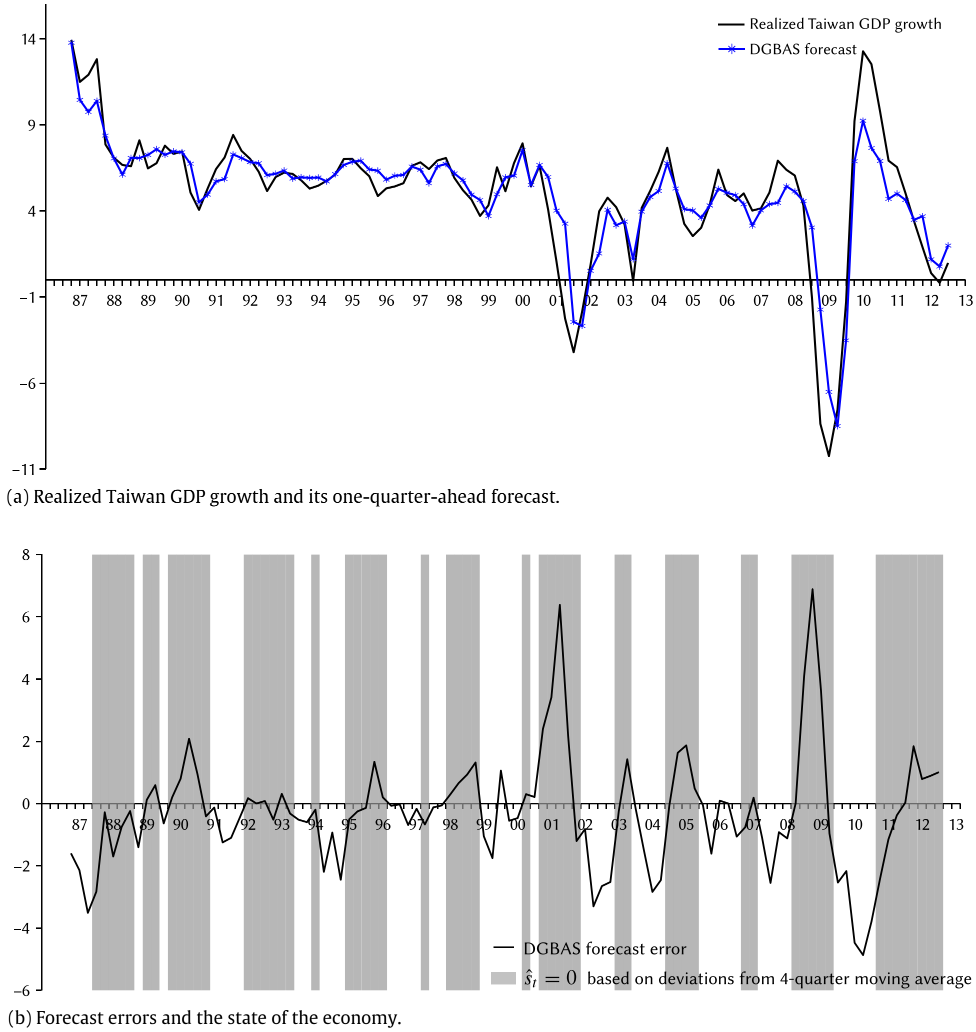

Fig. 1. Time series plots of Taiwan real GDP growth, DGBAS forecasts and forecast errors. The shaded areas in (b) satisfy $\hat{s}_t = 0$ based on deviations from a four-quarter moving average.

MZ regression (b1) and Nordhaus' model (c1) also indicate that the forecast is biased and inefficient, since the forecaster under-reacts to new information, and thus fails to incorporate all of the new information into the forecast. Moreover, the results of the state-dependent version of Nordhaus' model (c2) further show the time-varying biases for different states of the economy.

3.3. Results of the proposed model

We now analyze the dynamics of time-varying biases during different periods of the state of the economy using the proposed model (Eq. (6)).

Panel (A) in Table 2 presents the estimates, $\hat{\alpha}_0$, $\hat{\alpha}_1$, $\hat{\beta}_0$, $\hat{\beta}_1$, $\hat{\gamma}_\alpha^0$, $\hat{\gamma}_\alpha^1$, $\hat{\gamma}_\beta^0$ and $\hat{\gamma}_\beta^1$, say, that are obtained using the nonlinear least squares (NLS) estimation method. Panel (B) presents the results from testing Hypotheses 2.1 and 2.2 with χ^2 statistics using Wald joint tests, and Hypothesis 2.3 with t statistics using individual tests.

Panel (A) of Table 2 shows that the errors in the DGBAS forecast can be attributed to biases of under-estimation and under-reaction to news in different states of the economy. In particular, with respect to the bias that is caused by over/under-reactions to new information, an insignificant $\hat{\beta}_1$ with a significant $\hat{\beta}_0$ indicates that the forecaster reacts to news more accurately during periods of acceleration than deceleration; thus, under-reactions to news are an important source of forecast errors during decelerations. With respect to the bias that is generated by over-/under-estimation, the estimate $\hat{\alpha}_1$ is significantly negative, whereas $\hat{\alpha}_0$ does not differ from zero significantly. This indicates that the DGBAS only under-predicts GDP growth when GDP is accelerating. It is also worth noting that the goodness-of-fit measure $\bar{R}^2$ is 0.440, indicating that 44.0% of the variation in the forecast errors can be eliminated by considering the proposed biases.

The testing results in parts (I) and (II) of Panel (B) show that the DGBAS forecast is not optimal and suffers from state-dependent biases, which also suggests that

Table 1
Conventional unbiasedness and efficiency analyses.

Panel (A) Holden–Peel regression
Model (a1): $e_t = \mu + u_t$

Model	$\hat{\mu}$	Q (1)	Q (2)	Q (3)	Q (4)
(a1)	−0.303* (−1.694)	0.000***	0.000***	0.000***	0.000***

Note: The numbers in parentheses are robust t-statistics based on heteroscedasticity-consistent estimates for the corresponding variances; and $Q(r)$ denotes the Ljung–Box Q-statistic, with the corresponding probability value, that is used to test the null hypothesis of no autocorrelation of u_t for a specified order of autocorrelation lags r.
* Rejection at the 10% significance level.
*** Rejection at the 1% significance level.

Panel (B) Mincer–Zarnowitz regression
Model (b1): $y_t = \lambda + \delta y^f_{t|t-1} + u_t$

Model	$\hat{\lambda}$	$\hat{\delta}$	Joint test	$\bar{R}^2$
(b1)	−0.696 (−1.357)	1.197*** (14.447)	0.000***	0.819

Note: The numbers in parentheses are robust t-statistics based on heteroscedasticity-consistent estimates for corresponding variances; and the p-value of the joint test is for the null hypothesis $H_o : \lambda = 0, \delta = 1$.
*** Rejection at the 1% significance level.

Panel (C) Nordhaus regression
Model (c1): $e_t = \alpha + \beta \cdot FR_{t-1} + u_t$
Model (c2): $e_t = [\alpha_0 + \beta_0 \cdot FR_{t-1}] \times (1 - \hat{s}_{t-1}) + [\alpha_1 + \beta_1 \cdot FR_{t-1}] \times \hat{s}_{t-1} + u_t$

Model	$\hat{\alpha}$	$\hat{\alpha}_0$	$\hat{\alpha}_1$	$\hat{\beta}$	$\hat{\beta}_0$	$\hat{\beta}_1$	$\bar{R}^2$
(c1)	−0.433*** (−3.064)			−0.642*** (−4.620)			0.319
(c2)		0.050 (0.261)	−0.886*** (−4.299)		−0.499*** (−2.814)	−0.546** (−2.519)	0.361

Note: The numbers in parentheses are robust t-statistics based on heteroscedasticity-consistent estimates for the corresponding variances.
** Rejection at the 5% significance level.
*** Rejection at the 1% significance level.

Nordhaus' (1987) original model (Eq. (3)) may not be suitable for official forecasts in Taiwan. Since significant biases are revealed in Panel (A), part (III) of Panel (B) tests whether they are persistent. The p-values for the corresponding t-statistics suggest that $\gamma^0_\beta = 0$ is rejected significantly based on the data, while $\gamma^1_\alpha = 0$ is not. This implies that (i) the DGBAS persistently publishes forecasts of GDP growth that under-estimate the true value by 1.061% on average during periods of acceleration; (ii) the DGBAS under-reacts to new information during periods of deceleration; however, this bias is present for only 1.585 (=1/0.631) quarters on average,[8] with the degree of under-reaction diminishing with the duration.

3.3.1. Bias-corrected forecasts

Since the forecast errors of DBGAS, which can be attributed to possible over-/under-estimation or over-/under-reaction biases across the state of the economy, have been identified after estimating Eq. (6), the bias-corrected forecasts can now be made via Eq. (7):

$$y^{bc}_{t|t-1} = y^f_{t|t-1} - \hat{e}_t,$$

where $y^f_{t|t-1}$ is the forecast made by the DGBAS at time $t-1$, and $\hat{e}_t$ is the proposed estimate of e_t made using Eq. (6). As has been mentioned, this bias-corrected forecast is particularly useful for the real-time analysis, because a better forecast can be obtained immediately once a biased forecast has been released.

Fig. 2 plots the time series patterns of the bias-corrected forecast $y^{bc}_{t|t-1}$, along with the realized Taiwan GDP growth and the DGBAS forecasts from 1986Q4 to 2012Q3. Roughly speaking, the bias-corrected forecast $y^{bc}_{t|t-1}$ is much closer to the realized data than the DGBAS forecast $y^f_{t|t-1}$, especially during periods of deceleration after 2000. On average, 89.497% of the variation in the realized GDP growth can be explained by $y^{bc}_{t|t-1}$, whereas the DGBAS forecast explains only 79.857%; cf. Eq. (8).

In addition to the above (in-sample) performance of the proposed bias-corrected forecast, we now determine the effectiveness of this corrected forecast in pseudo out-of-sample experiments. Two competing classes of models are

[8] Recall that in exponential survivor functions, γ^0_β measures the fixed probability that the forecaster will leave the state of suffering from the under-reaction during periods of deceleration, with the expected duration of under-reaction being equal to $1/\gamma^0_\beta$ quarters.

Table 2
Estimation and hypothesis testing results.

Panel (A) Estimation results

Periods of deceleration			Periods of acceleration
(I) *Bias due to over-estimation or under-estimation*			
$\hat{\alpha}_0$	0.929	$\hat{\alpha}_1$	-1.061^{**}
	(0.402)		(−2.154)
$\hat{\gamma}_\alpha^0$	0.861	$\hat{\gamma}_\alpha^1$	0.071
	(0.394)		(0.466)
(II) *Bias due to over-reaction or under-reaction*			
$\hat{\beta}_0$	-2.913^{**}	$\hat{\beta}_1$	−0.267
	(−2.356)		(−0.862)
$\hat{\gamma}_\beta^0$	0.631^{***}	$\hat{\gamma}_\beta^1$	−0.197
	(3.165)		(−0.866)
$\bar{R}^2$		0.440	

Note: The numbers in parentheses are robust t statistics based on heteroscedasticity-consistent estimates of the corresponding variances.
** Rejection at the 5% significance level.
*** Rejection at the 1% significance level.

Panel (B) Hypothesis testings

	Statistics	p-value
(I) Hypothesis 2.1 (*optimal forecast*)	χ^2	
(a) $H_o: \alpha_0 = \alpha_1 = 0$	4.800^{*}	0.091
(b) $H_o: \beta_0 = \beta_1 = 0$	6.296^{**}	0.043
(c) $H_o: \alpha_0 = \alpha_1 = 0, \beta_0 = \beta_1 = 0$	14.446^{***}	0.006
(II) Hypothesis 2.2 (*state-independent bias*)	χ^2	
(a) $H_o: \alpha_0 = \alpha_1, \gamma_\alpha^0 = \gamma_\alpha^1$	1.729	0.421
(b) $H_o: \beta_0 = \beta_1, \gamma_\beta^0 = \gamma_\beta^1$	7.484^{**}	0.024
(c) $H_o: \alpha_0 = \alpha_1, \gamma_\alpha^0 = \gamma_\alpha^1, \beta_0 = \beta_1, \gamma_\beta^0 = \gamma_\beta^1$	8.940^{*}	0.063
(III) Hypothesis 2.3 (*persistent bias*)	t	
(a) $H_o: \gamma_\alpha^1 = 0$	0.466	0.641
(b) $H_o: \gamma_\beta^0 = 0$	3.165^{***}	0.002

Note: A joint Wald test with χ^2 statistics is employed for testing Hypotheses 2.1 and 2.2, while individual tests with t statistics are used for Hypothesis 2.3.
* Rejection at the 10% significance level.
** Rejection at the 5% significance level.
*** Rejection at the 1% significance level.

compared below. The first class contains three MZ bias-adjusted models based on modifications of the work of Ang et al. (2007). They are

$$\text{MZ1: } y_t = \lambda + \delta y^f_{t|t-1} + \varepsilon_t;$$

$$\text{MZ2: } y_t = \lambda_{10} \times \left(1 - \hat{s}_{t-1}\right) + \lambda_{11} \times \hat{s}_{t-1} + \delta_1 y^f_{t|t-1} + \varepsilon_t;$$

$$\text{MZ3: } y_t = \left[\lambda_{20} + \delta_{20} y^f_{t|t-1}\right] \times \left(1 - \hat{s}_{t-1}\right) + \left[\lambda_{21} + \delta_{21} y^f_{t|t-1}\right] \times \hat{s}_{t-1} + \varepsilon_t,$$

where MZ1 is the conventional MZ regression, while MZ2 and MZ3 are two generalizations that depend on the proxy for the economic state $\hat{s}_{t-1}$.

The second class consists of linear/nonlinear autoregressive time series models, namely the typical linear autoregressive time series model:

$$\text{yAR}(p)\text{: } y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \varepsilon_t,$$

where $1 \leq p \leq 5$, and the nonlinear exponential smooth transition autoregressive (ESTAR) model:

$$\text{yESTAR}(q)\text{: } y_t = a_0 + \sum_{j=1}^{q} \varphi_{0j} y_{t-j} + \left(a_1 + \sum_{j=1}^{q} \varphi_{1j} y_{t-j}\right) \times G(\gamma, \mu, y_{t-1}) + \varepsilon_t,$$

where

$$G(\gamma, \mu, y_{t-1}) = \left[1 + \exp\{-\gamma(y_{t-1} - \mu)\}\right]^{-1},$$

and $1 \leq q \leq 5$.

We consider fifty-one pseudo out-of-sample periods from 2000Q1 to 2012Q3 (about a half of the full sample period). A recursive estimation scheme is utilized for all regressions on the samples, beginning in 1986Q4 and ending between 1999Q4 and 2012Q2. That is, the first estimation begins with data from 1986Q4 to 1999Q4, and a one-step-ahead forecast for 2000Q1 is made based on these estimates; the second estimation and the resulting one-step-ahead forecast for 2000Q2 are based on the data from 1986Q4 to 2000Q1, and so on. Hence, the final forecast for 2012Q3 is made based on data ending in 2012Q2. Notably, the optimal lag lengths p for the yAR(p) model and q for the yESTAR(q) are also determined recursively by applying the Baysian information criterion (BIC) to each sample period. The models' performances

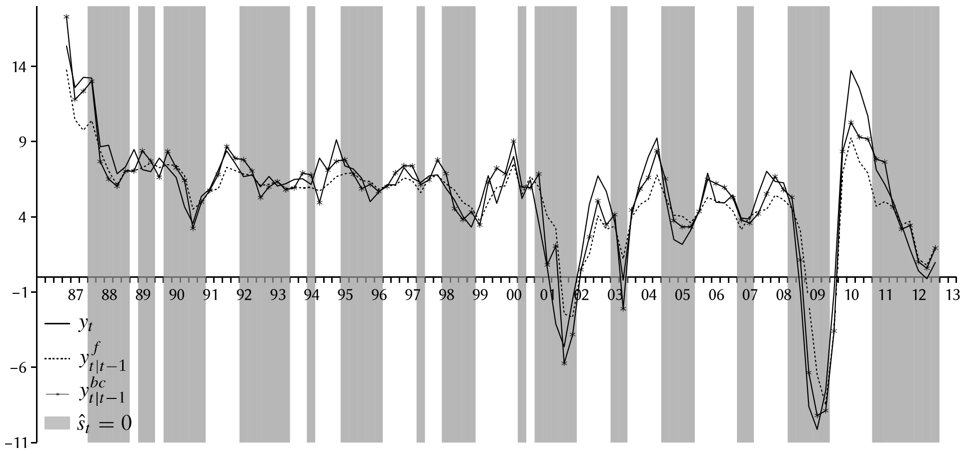

Fig. 2. Time series plots of realized Taiwan GDP growth, the DGBAS forecast and the bias-corrected forecast $y^{bc}_{t|t-1}$. The shaded area represents decelerating periods where $\hat{s}_t = 0$ for all t.

Table 3
Out-of-sample performance comparisons.

	DGBAS	Bias-corrected model	MZ bias-adjusted models			Autoregressive models	
	$y^f_{t\|t-1}$	$y^{bc}_{t\|t-1}$	MZ1	MZ2	MZ3	yAR(p)	yESTAR(q)
MSE	5.669	3.477	5.602	4.738	5.283	5.952	7.964
MAE	1.762	1.472	1.772	1.615	1.676	1.925	2.036
DM_S		−2.454***	−0.087	−1.175	−0.396	0.252	1.108
(p-value)		(0.007)	(0.465)	(0.120)	(0.346)	(0.600)	(0.866)
DM_A		−2.115***	0.073	−1.009	−0.508	0.731	0.939
(p-value)		(0.017)	(0.529)	(0.156)	(0.306)	(0.768)	(0.826)

Note: The null and alternative hypotheses for DM tests are H_0: "there is no difference in forecast accuracy between the competing forecast and the DGBAS forecast", and H_1: "the competing forecast is superior to the DGBAS forecast", DM_S are the corresponding statistics calculated by square error differences, while DM_A are based on absolute error differences.
*** Rejection at the 1% significance level.

are measured in terms of the mean square error (MSE) and mean absolute error (MAE), and Diebold and Mariano's (1995) test (the DM test hereafter) is also implemented for comparing the performances of these six models with that of DGBAS. The null hypothesis of the DM test is that there is no difference between the forecast accuracies of the competing forecast and the DGBAS forecast, while the alternative is that the competing forecast is superior. Two test statistics, one for the squared error differences (DM_S) and another for the absolute error differences (DM_A), are computed.

Table 3 summarizes the results. First, the DM tests do not support the hypothesis that the three MZ-type adjusted forecasts and the two autoregressive-type forecasts are significantly superior to the DGBAS forecast, even though some of their MAEs and MSEs are slightly lower than those of DGBAS. Second, the proposed bias-corrected forecast is better than those made using any of the other models, because it has the lowest MSE and MAE values. The bias-corrected forecast has a MSE that is 38.67% lower than that of the DGBAS forecast and a MAE that is 16.46% lower, as it eliminates possible over-/under-estimation and over-/under-reaction biases in different states of the economy. Furthermore, both DM tests significantly reject the null hypothesis in favor of the alternative hypothesis that the bias-corrected forecast is superior to Taiwan's official forecast.

3.4. Robustness checks for state proxy and long horizon forecasts

We also conduct robustness checks by using two alternative state proxies where six-quarter and eight-quarter MAs in Eq. (5) are adopted. The resulting inferences are essentially the same.

On the other hand, longer horizon forecast errors are also considered in addition to the one-step-ahead forecast errors. The model for the h-step-ahead forecast is established as

$$\begin{aligned} e_{t,h} = &\left[\alpha_0 \exp\left(-\gamma^0_\alpha \cdot \hat{d}^0_{t-h}\right) + \beta_0 \exp\left(-\gamma^0_\beta \cdot \hat{d}^0_{t-h}\right) FR_{t-h}\right] \times \left(1 - \hat{s}_{t-h}\right) \\ &+ \left[\alpha_1 \exp\left(-\gamma^1_\alpha \cdot \hat{d}^1_{t-h}\right) + \beta_1 \exp\left(-\gamma^1_\beta \cdot \hat{d}^1_{t-h}\right) FR_{t-h}\right] \times \hat{s}_{t-h} + u_{t,h}, \end{aligned}$$

where $e_{t,h} = y^f_{t|t-h} - y_t$ and $FR_{t-h} = y^f_{t|t-h} - y^f_{t|t-h-1}$. Here, we analyzed the two- and three-step-ahead forecasts. In brief, the estimation and testing results show that the state-dependent biases in the two-step-ahead DGBAS forecast are weak, while those in the three-step-ahead DGBAS forecasts are statistically significant and persistent. We do not report detailed results here, owing to space limitations.

4. Concluding remarks

This paper aims to investigate whether or not forecasts are optimal, given the information that was available when the forecasts were made. Going beyond the papers that study forecast errors based on the model of Nordhaus (1987), we use a time-varying procedure to forecast revisions, and also account for the possibility that the duration of the state may affect the bias as well. Three testable hypotheses are presented to help researchers test the optimality of forecasts, with the ultimate aim of determining whether or not these biases depend on the underlying economic state and are persistent over the duration of the state. The corresponding bias-corrected forecasts can then be made based on these results. Briefly, this framework is novel and can be implemented using conventional estimation and hypothesis methods.

In the empirical part, we apply the proposed framework to an investigation of Taiwan's DGBAS forecasts for GDP growth rates. We find that the one-quarter-ahead forecast is not optimal, but actually suffers from state-dependent biases: a persistent under-estimation bias in the relatively good state and an under-reaction bias that decays with the duration in the relatively bad one. Eliminating these biases from the DGBAS forecast can remove over 44.0% of the variation in forecast errors, and pseudo out-of-sample experiments further support the fact that the resulting bias-corrected forecasts are markedly better than either those made by Taiwan's government or those made using other competing models.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at http://dx.doi.org/10.1016/j.ijforecast.2015.11.016.

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