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Abstract

This paper evaluates the efficiency of the Japanese fiscal authority's revenue projections from 1960 to 2020 using real-time data. Revenue projections are not efficient, primarily due to the conditioning projections of output growth. By adjusting the forecasts based on the results of real-time forecast evaluations, this paper finds that the out-of-sample accuracy of the one-year-ahead projections could be significantly improved by a magnitude of up to 10 percent in root mean squared errors. The analysis of the disaggregated series suggests that corporate tax projections are the least efficient. The fiscal authority's loss function is estimated to be asymmetric, making the underprediction of revenues more common.

Keywords: Revenue Projections, Japan, Forecast Evaluation, Real-Time Data, Out-of-Sample Forecast Accuracy

J.E.L. codes: C53, E62, H68

1 Introduction

Governments produce fiscal projections in their national budgets to maintain accountability for the use of public funds. As noted by Elmendorf (2015), fiscal projections are essential inputs to debates about national budgets and play a critical role in the formulation of fiscal policy. Although the accuracy of fiscal projections has a substantial impact on a nation's economic well-being, evaluations of fiscal projections are scarce compared to those of macroeconomic projections, perhaps due to their political nature and short sample period. This issue has been widely recognized in the literature, and a growing number of papers focus on evaluations of fiscal projections.[1] However, these analyses primarily focus on US data, and international evidence remains limited.

To fill this gap, this paper evaluates the efficiency of revenue projections made by Japan's fiscal authority. Japan has a relatively long sample of fiscal projections from 1960 to 2020, with corresponding real-time data, which enables us to make a fair comparison with evaluations of the US. We primarily focus on revenue projections for two reasons. First, although the public pays particular attention to deficit projections due to concerns about fiscal sustainability, errors in deficit projections are largely driven by errors in revenue projections. The findings in the literature suggest that forecasting fiscal revenue is inherently more difficult than outlays because revenues depend on macroeconomic fundamentals that become nearly unpredictable, as documented in Buettner and Kauder (2010).[2] Second, many fiscal authorities make systematic mistakes in their revenue forecasting, often overestimating revenue.[3] Investigating whether the Japanese fiscal authority has similar tendencies in its revenue projections is an interesting, but as yet unanswered, question.

To answer this question, this paper employs the standard methods of forecast evaluations proposed by Mincer and Zarnowitz (1969) and Patton and Timmermann (2012), which test whether

[1]For example, Kliesen and Thornton (2001, 2012) evaluate fiscal projections made by the Congressional Budget Office (CBO), and Croushore and van Norden (2018, 2019) analyze fiscal projections made by the Federal Reserve. Ericsson and Martinez (2019) and Martinez (2015) provide evaluations of projections for federal debt in the US. See Auerbach (1999) and Campbell and Ghysels (1995) for earlier studies.

[2]For example, it has been extremely difficult to outperform simple reduced-form models forecasting output growth in recent decades, as documented in Edge and Gürkaynak (2010), Faust and Wright (2013), and Tulip (2009).

[3]For example, Booth et al. (2015) find that the CBO's revenue projections have an upward bias, and Leal et al. (2008) document similar overoptimism in a study of EU member countries. See Frankel (2011) for cross-country evidence of overoptimism.

forecast errors and forecast revisions are predictable. This paper also uses the additional methodology proposed by Faust and Wright (2008) to control the effects of conditioning variables. The analysis is based on a recently built real-time data set, which is critical for forecast evaluation, as documented in Cimadomo (2016) and Croushore (2006).

The results of forecast evaluations show that the efficiency of revenue projections is significantly rejected, particularly for one-year-ahead forecasts, with a positive bias and slope coefficient significantly smaller than unity. Unlike the US or EU member countries, the Japanese fiscal authority tends to underestimate revenues. This inefficiency seems to be primarily due to projections made during recessions. However, efficiency is accepted once output growth projections are controlled as a conditioning variable.

Based on the rejection of forecast efficiency, this paper employs a method proposed by Croushore (2012) to adjust the systematic errors of forecasts in real time. The rejection of forecast efficiency implies that a forecaster makes systematic mistakes. Since forecast evaluations incorporate these systematic mistakes, forecast accuracy could potentially be improved by collecting the predicted values, which effectively corrects past systematic mistakes in real time. We show that the out-of-sample accuracy of one-year-ahead revenue projections can be significantly improved by a magnitude of up to 10 percent in root mean squared errors (RMSEs) in recursive and rolling methods. However, there is no significant improvement in nowcasts, perhaps because the forecast errors are not systematic.

This paper provides two additional exercises to shed light on the sources of inefficiency. It analyzes the disaggregated series of revenues—income, corporate, and consumption taxes—between 1989 and 2020. The efficiency of corporate tax projections is rejected, while those of income tax and consumption tax are not. We also estimate the asymmetry of a forecaster's loss function by applying the methods proposed by Elliott et al. (2005). The fiscal authority's loss function is estimated to be asymmetric, showing a greater aversion to negative forecast errors and implying that the underprediction of revenues is more common.

The contribution of this paper is twofold. First, it provides the first comprehensive assessment of fiscal projections in Japan, employing methods of forecast evaluations based on real-time data. The results are consistent with the literature documenting problems in official Japanese macroeconomic forecasts—strong inefficiency and inferior performance relative to private forecasters.[4] These results could be interpreted as evidence of manipulations in budgetary projections based on political motives, such as in Paleologou (2005) for the UK, Pina and Venes (2011) for EU countries, and Maekawa and Fukushige (2012) for Japan.

Second, this paper provides additional evidence that the results of forecast evaluations could be used to improve the accuracy of forecasts in real time, particularly when efficiency is rejected. Several studies find that policy institutions' forecasts can be improved in real time by adjusting systematic errors,[5] which is also the case for the Japanese fiscal authority.

The remainder of this paper is organized as follows: Sections 2 and 3 set out the data and methods used. Section 4 presents the results of the efficiency evaluation. Section 5 provides the extensions, and Section 6 offers concluding remarks.

2 Data

In this paper, we focus on Japanese revenue projections normalized by real-time nominal output from 1960 to 2020. The revenue projections are based on a fiscal year in Japan (from April to March), and the timing is illustrated in Figure 1. The first projections are released before the fiscal year starts, typically in December of the previous year, together with a proposal for the annual budget. Then, the fiscal authority updates its projections in the middle of the fiscal year, typically between October and December, which can be regarded as nowcasts. After the fiscal year ends, the government publishes the realized values of revenues, typically in November.

Nominal output is obtained from the real-time data set compiled by Komaki (2009) and the Tokyo Foundation for Policy Research. The base of output is GNP before 1990 and GDP thereafter. The data between 1960 and 1968 are based on the vintage observed in 1969 due to the lack of older vintages. The level of nominal GDP in a fiscal year is computed by adding the corresponding quarterly GDP observed two quarters after the end of the fiscal year, following the convention proposed by Reifschneider and Tulip (2007) and Faust and Wright (2009).[6]

[4] For example, see Ashiya (2003, 2007), and Tsuchiya (2016).

[5] For example, Arai (2014, 2020) finds significant improvement in out-of-sample forecast accuracy in the Federal Reserve's inflation forecasts and the CBO's revenue projections.

[6] More recently, Reifschneider and Tulip (2019) adopt an adjustment based on the current vintage, which has only

We also use real output growth as the conditioning variable, which is computed by taking percentage change relative to the previous year. The rationale for this computation is consistency with the government's output growth projections. As for nominal GDP, the computation is based on the vintage observed two quarters after the fiscal year ends. Election and recession dummies are used as additional control variables. Election dummies take the value of 1 when a lower house election is held during a fiscal year. For the recession dummies, we use the number of months classified as a recession in a fiscal year, normalized by 12 months. The classification of business cycles is based on official releases by the Economic and Social Research Institute of the Cabinet Office.

Figure 2 shows the time series of forecast errors of one-year-ahead projections and nowcasts. As is evident from the figure, the variation in one-year-ahead forecast errors is substantially larger than that of nowcasts, ranging between -2.5 and 2 percent of nominal GDP.

3 Methodology

The methodology used in this paper is threefold: (1) forecast evaluation with a symmetric loss function, (2) conditional forecast evaluation, and (3) real-time adjustment based on forecast evaluation. The notation follows Arai (2020).

3.1 Forecast Evaluation with a Symmetric Loss Function

We start with the Mincer-Zarnowitz (MZ) evaluation based on the assumption of a symmetric loss function. Let y_{t+h} be a variable at time $t+h$ to be forecasted and let $\hat{y}_{t+h|t+j}$ be a forecast of y_{t+h} at time $t+j$ for any $0 < j < h$. An optimal forecast, $\hat{y}^*_{t+h|t+j}$, should minimize the expected loss of the forecasts, $L(\cdot)$, which is a function of the forecast errors in the available information set Ω_{t+j} as follows:

$$\hat{y}^*_{t+h|t+j} = \underset{\hat{y}_{t+h|t+j}}{\arg\min}\, E[L(e_{t+h|t+j})|\Omega_{t+j}], \tag{1}$$

modest implications in terms of magnitude.

where $e_{t+h|t+j} \equiv y_{t+h} - \hat{y}_{t+h|t+j}$. By assuming the mean squared error loss function and taking the first-order condition,[7] we derive the following optimality condition:

$$\hat{y}^*_{t+h|t+j} = E[y_{t+h}|\Omega_{t+j}]. \tag{2}$$

This condition implies that the optimal forecasts should be the conditional mean of the series. Based on this implication, Mincer and Zarnowitz (1969) proposed the following regression to evaluate the efficiency of forecasts:

$$y_{t+h} = \alpha + \beta \hat{y}_{t+h|t+j} + \varepsilon_{t+h}, \tag{3}$$

thereby jointly testing the null hypothesis that there is no bias in the forecasts ($\alpha = 0$) and that the relationship between the forecasts and the realized values is one-to-one ($\beta = 1$).

More recently, Patton and Timmermann (2012) (PT) proposed a more powerful forecast efficiency evaluation at multiple horizons, testing the internal consistency of the forecasts. We first define the forecast revision for period $t+h$ between t and $t+j$, as $r_{t+h|t,t+j} \equiv \hat{y}_{t+h|t+j} - \hat{y}_{t+h|t}$. By replacing the forecast in Equation (3) with the sum of the forecast at a longer horizon and subsequent revisions, $\hat{y}_{t+h|t+j} = \hat{y}_{t+h|t} + \sum_{k=1}^{j} r_{t+h|t+k-1,t+k}$, Equation (3) can be rewritten as follows:

$$y_{t+h} = \alpha + \beta \; \hat{y}_{t+h|t} + \sum_{k=1}^{j} \gamma_k \; r_{t+h|t+k-1,t+k} \; + \varepsilon_{t+h}, \tag{4}$$

with the null hypothesis of $[\alpha, \beta, \gamma_1, \dots, \gamma_j] = [0, 1, 1, \dots, 1]$, where j denotes the number of forecast revisions included in the regression. Unlike the MZ regression, this PT regression jointly tests the implications of forecast efficiency that both forecast errors and forecast revisions are orthogonal to past forecasts.

3.2 Conditional Forecast Evaluation

The forecast evaluations discussed in the previous subsection assume that forecasters make unconditional forecasts, allowing us to test the unpredictability of forecast errors and revisions. However,

[7] For details, see Chapter 15 of Elliott and Timmermann (2016).

many economic forecasts are conditional in nature, in the sense that they are based on a particular path of conditioning variables. For example, revenue projections may need to be consistent with government's official macroeconomic projections, which are revised slowly. Such restrictions on conditioning forecasts may lead to endogeneity issues in forecast evaluations.

To mitigate these issues, we employ the method of conditional forecast evaluation proposed by Faust and Wright (2008) (FW). We decompose the observed conditional forecasts into two components: optimal forecasts and the deviation in the conditioning assumptions from the optimal forecasts. After controlling for the differences in the conditioning assumptions, we test the unpredictability of unconditional forecast errors.

Suppose that the fiscal variable y_t depends on the $m \times 1$ vector of conditioning macroeconomic variables, $\mathbf{z_t}$. The conditional forecasts for y_{t+h} and $\mathbf{z_{t+h}}$ at time t are denoted as $\hat{y}^c_{t+h|t}$ and $\hat{\mathbf{z}}^c_{t+h|t}$, respectively. For simplicity, assume that the deviation of conditional fiscal forecasts from the optimum is linearly associated with the corresponding deviations in the conditioning macroeconomic forecasts as follows:

$$\hat{y}^c_{t+h|t+j} - \hat{y}^*_{t+h|t+j} = \boldsymbol{\theta}'(\hat{\mathbf{z}}^c_{t+h|t+j} - \hat{\mathbf{z}}^*_{t+h|t+j}). \tag{5}$$

In other words, the observed conditional forecasts deviate from the optimal forecasts because of the deviation in the conditioning assumptions. By combining this decomposition with the MZ forecast evaluation in Equation (3), the baseline regression is rewritten as follows:

$$y_{t+h} = \alpha + \beta\hat{y}^c_{t+h|t+j} + \boldsymbol{\delta}'(\hat{\mathbf{z}}^c_{t+h|t+j} - \hat{\mathbf{z}}^*_{t+h|t+j}) + \varepsilon_{t+h}, \tag{6}$$

where $\boldsymbol{\delta} = -\beta\boldsymbol{\theta}$, with a null hypothesis of $\alpha = 0$ and $\beta = 1$. As in the MZ evaluation, this null hypothesis jointly tests whether there is no bias and the relationship between the forecasts and the realized values is one-to-one. The only difference from the MZ evaluation is that we control the deviation from the optimal forecasts in the path of conditioning assumptions to effectively test the unpredictability of unconditional forecast errors. Note that there is no testable implication for $\boldsymbol{\delta}$, as it simply controls the deviations in the conditioning assumptions. Since the availability of unconditional conditioning forecasts ($\hat{\mathbf{z}}^*_{t+h|t+j}$) is limited, we replace it with the realized value

$(\mathbf{z}_{t+h|t})$ for the estimation.

3.3 Real-Time Adjustment Based on Forecast Evaluation

Based on the results of the forecast evaluation, we conduct a real-time forecasting exercise to see whether the evidence against efficiency can be used to improve the accuracy of forecasts. Suppose that we run the MZ evaluation described in Equation (3) at time t. Then, we define the adjusted forecast $\tilde{y}_{t+h|t}$ as the predicted value of forecast evaluation as follows:

$$\tilde{y}_{t+h|t} \equiv \hat{\alpha}_t + \hat{\beta}_t \hat{y}_{t+h|t}, \tag{7}$$

where $\hat{\alpha}_t$ and $\hat{\beta}_t$ are the estimates based on the data vintage available at time t.[8] The idea behind this adjustment is that the regression coefficients of the forecast evaluation capture the systematic mistakes that a forecaster made in the past, which can be used to correct the systematic tendency in the most recent forecast. We form the adjusted forecast in real time by repeating this procedure for every period to obtain predictions from the forecast efficiency evaluation.

4 Empirical Results

The results of the MZ evaluation are summarized in Table 1. The efficiency of the one-year-ahead forecast is strongly rejected by the MZ evaluation, with positive biases and slopes significantly smaller than 1 for multiple specifications. This result suggests that revenue projections tend to be systematically smaller than realized values. In other words, the Japanese fiscal authority tends to underestimate revenues, unlike the CBO in the US or the fiscal authorities of EU member states. Although the additional control variables of election or recession months are not statistically significant, the bias (2.11) and the coefficient on forecasts (0.83) in no recession periods are not significantly different from the values in the null hypothesis in the specification with recession dummies. In contrast, the bias (3.34) and the coefficient on forecasts (0.62) in recession periods further deviate from the values in the null hypothesis. This result sugges1ts that the projections

[8] Since annual nominal GDP is available approximately two years after the first revenue forecasts are released, we conduct the forecast evaluations using the data until period $t-2$ to adjust the forecast made at period t.

made during recessions may contribute to inefficiency.

For nowcasts, the overall efficiency is rejected, although individual coefficients are not statistically different from the values in the null hypothesis. Figure 3 compares the scatterplots of forecasts, nowcasts, and realized values to show the contrast between forecasts and nowcasts. As is evident from the figure, the deviation of the estimated slope from the 45-degree line is larger for forecasts than for nowcasts, and the fluctuations of forecasts are substantially larger than those of nowcasts, which likely reflects the information advantage in nowcasts.[9]

Table 2 provides the results of the PT and FW evaluations. The joint efficiency of revenue projections that combine forecast errors and forecast revisions are strongly rejected by the PT evaluation. The results of the FW evaluation show that both forecasts and nowcasts become efficient once the forecast errors of the corresponding output growth projections are controlled. These results imply that the inefficiency of revenue projections is mainly due to the inefficiency of output growth projections, which are conditioning variables for revenue projections. These results are similar to those of Arai (2020), which analyzes the CBO's budgetary projections.

Table 3 presents the relative RMSEs of the different forecasting models compared to the original forecast: the random walk model, the AR(1) model, the adjusted forecasts based on the MZ evaluation, and the adjusted forecasts based on the vector-MZ evaluation. The most recent realized value is treated as a forecast for the random walk model. The AR(1) model is estimated using the vintage of realized values, and we take the prediction from the most recent observation as the forecast. The MZ-adjusted forecasts are based on the MZ evaluation of revenue projections described in Equation (7). The vector-MZ-adjusted forecasts are based on the joint MZ evaluation of revenue and output growth projections—we extend the framework in Equation (3) into multiple series. Then, we take the prediction of revenue projections as the adjusted forecast. The first 31 years are used as a training period, and we compare the out-of-sample forecasting performance after the training period with recursive and rolling estimations. The results show that the adjustment significantly improves the accuracy of the one-year-ahead forecasts by a magnitude of up to 10 percent in RMSEs. These results imply that the fiscal authority makes a systematic mistake for the one-year-ahead revenue projections and that correcting such mistakes makes the forecasts more

[9] This result is consistent with the discussion in Faust and Wright (2013) and Bańbura et al. (2013), which highlight the different natures of forecasts and nowcasts in practice.

accurate in real time.

In contrast, the adjustment does not improve the accuracy of nowcasts. This is because the inefficiency of nowcasts is neither strong nor systematic, and the adjustment based on forecast evaluations cannot improve forecast accuracy. In fact, the original nowcasts are far more accurate than the random walk or the AR(1) model, suggesting that the fiscal authority successfully exploits the information advantage of nowcasts to produce more accurate forecasts. The recursive and rolling estimations lead to similar results, which implies that the results are robust.

5 Extensions

To shed light on the source of inefficiency, we provide two extensions to the main results: an evaluation of disaggregated revenue projections and an estimation of the asymmetry of the fiscal authority's loss function.

5.1 Evaluation of Diaggregated Revenue

We present the results of the MZ evaluation of the disaggregated series of revenues from 1989 to 2020 in Table 4—income, corporate, and consumption taxes. The analysis of the disaggregated series suggests that the efficiency of corporate tax is significantly rejected, while those of income tax and consumption tax are not. Although none of these tax projections has significant biases, the slope of the corporate tax projections is 0.69 for forecasts and 0.85 for nowcasts, which leads to the rejection of efficiency.[10] The inefficiency of corporate tax projections is consistent with the results of the conditional forecast evaluations—corporate tax is more sensitive to macroeconomic conditions than the other taxes, and the inefficiency of macroeconomic projections leads to the inefficiency of corporate tax projections. This result is similar to results in the US, where corporate tax projections exhibit the largest forecast errors, as discussed by Booth et al. (2015).

[10]The rejection of efficiency is less severe relative to the whole sample, which is likely due to the lower power of the tests with the short sample.

5.2 Estimation of an Asymmetric Loss Function

We then estimate the asymmetry of a forecaster's loss function using the methodology proposed by Elliott et al. (2005). Suppose that the forecaster has a piecewise asymmetric loss function as follows:

$$L(e_{t+h|t+j}) \equiv [\alpha + (1-2\alpha)\mathbb{1}(e_{t+h|t+j} < 0)]|e_{t+h|t+j}|^p, \tag{8}$$

where a larger deviation of α from 0.5 indicates a greater aversion to positive forecast errors. Elliott et al. (2005) assume that a forecaster follows a systematic forecasting rule, $f(\theta)$, where θ governs the weights of the variables in the information set. A simple example is the linear forecasting rule $f(\theta) = \theta' \mathbf{V}_{t+j}$, where $\mathbf{V}_{t+j}$ are the variables in the information set at $t+j$. By following a similar discussion of the MZ evaluation and deriving the first-order condition, the optimal forecast to minimize the expected loss leads to the following moment condition :

$$E[\underbrace{\mathbf{V}_{t+j}(\mathbb{1}(e_{t+h|t+j} < 0) - \alpha)|e_{t+h|t+j}|^{p-1}}_{\equiv \mathbf{g}_{t+j}(\alpha)}] = \mathbf{0}. \tag{9}$$

By exploiting this moment condition,[11] α can be estimated by the generalized method of moments (GMM) as follows:

$$\hat{\alpha} = \arg\min_{\alpha} \mathbf{g}_T(\alpha)' \mathbf{W} \mathbf{g}_T(\alpha), \tag{10}$$

where $\mathbf{g}_T(\alpha) = \sum_{t=1}^{T} \mathbf{g}_{t+j}(\alpha)$, and W is an appropriate weighting matrix.

Table 5 shows the GMM estimates of an asymmetric loss function based on a different combination of instruments, including constant, past forecasts, past forecast errors, and past output growth forecasts. The null hypothesis of the symmetric loss function is significantly rejected in all specifications, with estimates smaller than 0.5. Based on the results of the J-statistics, we do not reject the null that our instruments are exogenous. The estimated parameters of the loss function imply that a forecaster shows a greater aversion to negative forecast errors, which is consistent with the results of the MZ evaluation with positive biases. This result also suggests that the Japanese fiscal authority tends to underpredict revenues and avoid a projection of surplus, unlike the authorities

[11] V_{t+j} is replaced by $f'(\theta)$ if the forecasting rule is nonlinear.

in the US or in EU member countries who tend to be overoptimistic.

6 Conclusion

In this paper, we provide a comprehensive evaluation of the Japanese fiscal authority's revenue projections from 1960 to 2020 and find several sets of results. First, the efficiency of revenue projections is strongly rejected, particularly for the one-year-ahead forecast, which is likely due to inefficiency in conditioning forecasts. Then, we show that evidence against efficiency can be used to improve the accuracy of forecasts in real time by correcting past systematic mistakes. By studying disaggregated projections, we find that corporate tax projections are the least efficient. Finally, the Japanese fiscal authority's loss function is estimated to be asymmetric, preferring the underprediction of revenues.

Given the highly political nature of revenue projections that involve the discussion of the national budget, it may be possible that the Japanese fiscal authority has a particular preference for under/over predictions of revenue, which leads to the rejections of efficiency revealed in this paper. However, maintaining such systematic errors may undermine the credibility of revenue projections in the long run. Providing a comprehensive evaluation of forecast efficiency is crucial to controlling the quality of forecasts. Since the proposed adjustment based on forecast evaluations is fairly straightforward to implement, policy institutions could consider this adjustment a viable option for their forecasting and evaluations.

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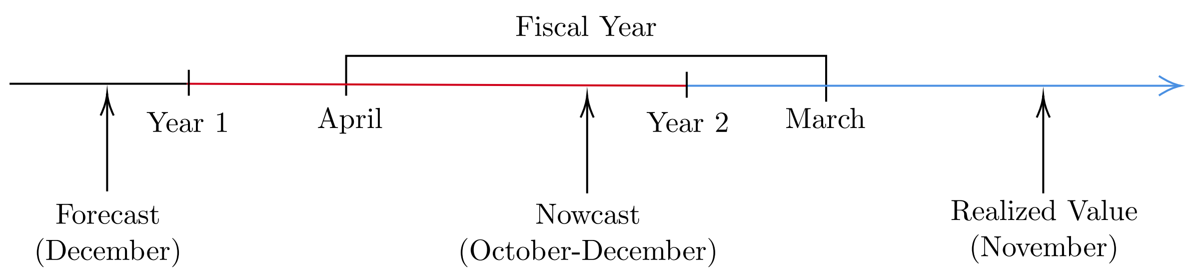


Note: This figure illustrates the timeline of revenue projections made by the Japanese fiscal authority and its relationship with the Japanese fiscal year.

Figure 1: Timeline of Revenue Projections

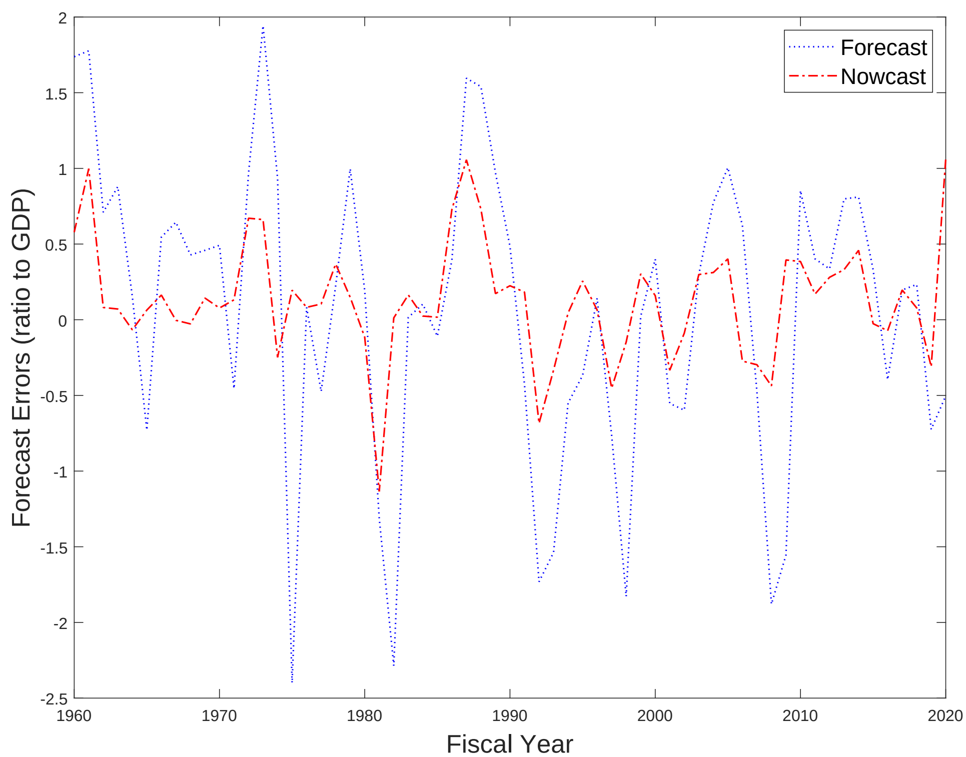
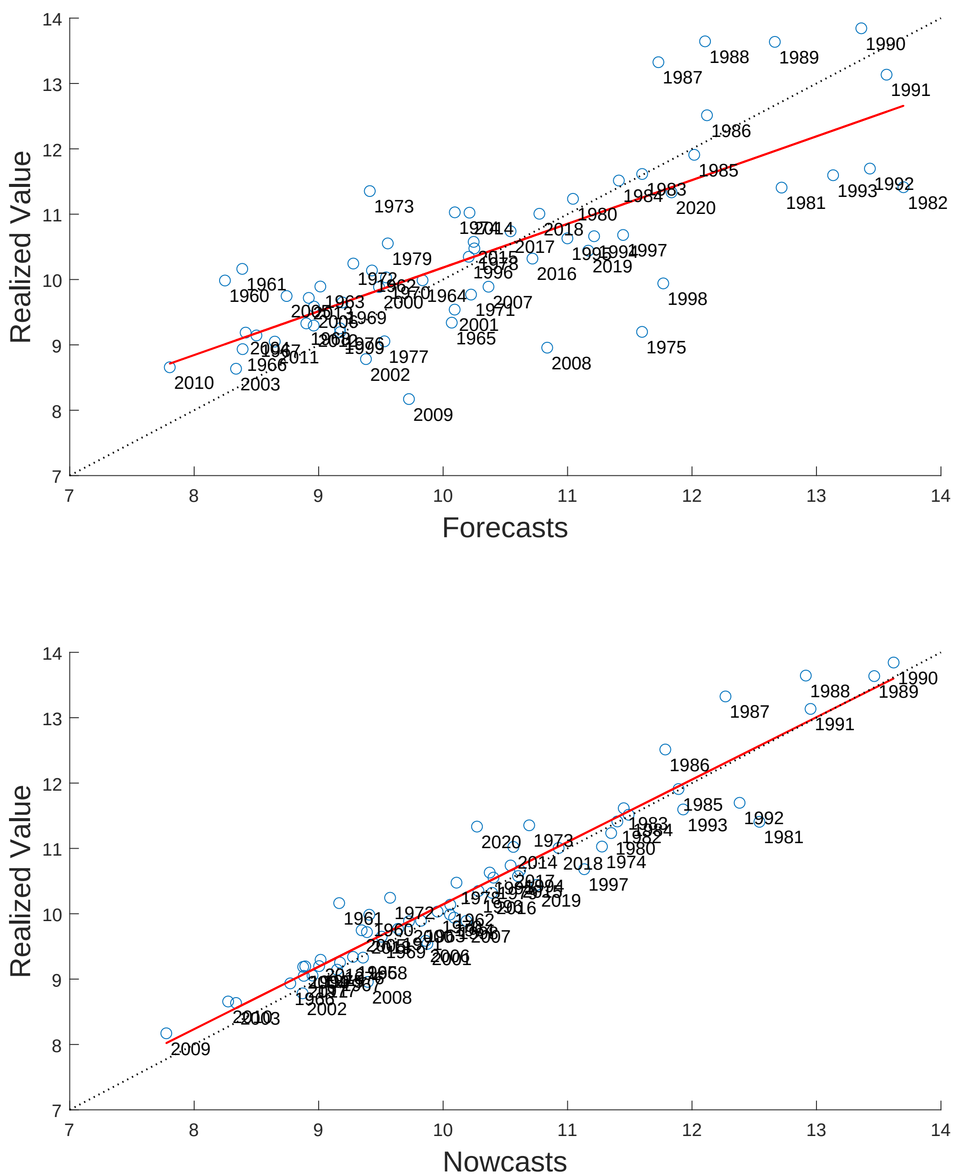


Figure 2: Forecast Errors of Revenue Forecasts



Note: The black dotted line is the 45-degree line, and the red solid line is the linear fitted line.

Figure 3: Forecasts, Nowcasts, and Realized Values

	Forecasts			Nowcasts		
Specification	(1)	(2)	(3)	(1)	(2)	(3)
Estimates:						
Constant	3.49**	3.65**	2.11	0.59	0.46	0.05
	(1.05)	(1.13)	(1.10)	(0.56)	(0.72)	(0.44)
Forecasts	0.67**	0.65**	0.83	0.95	0.96	1.01
	(0.11)	(0.11)	(0.12)	(0.06)	(0.04)	(0.05)
Election		−1.03			0.26	
		(1.22)			(0.60)	
Election×Forecasts		0.13			−0.01	
		(0.12)			(0.06)	
Recession			1.23			1.65
			(1.57)			(1.00)
Recession×Forecast			−0.21			−0.16
			(0.15)			(0.10)
Wald Statistic	15.38**	20.09**	49.09**	12.58**	36.59**	16.40**
Adjusted R^2	0.59	0.59	0.66	0.92	0.92	0.92

[a.] This table shows the results of the MZ forecast evaluation in Equation (3) with the additional control variables of election and recession dummies.

[b.] Heteroscedasticity and autocorrelation robust (HAC) standard errors are listed in parentheses. ** denotes the significance at the level of 1 percent.

Table 1: MZ Evaluations of Revenue Projections (1960–2020)

	PT Evaluation	FW Evaluation	
		Forecasts	Nowcasts
Estimates:			
Constant	0.64	0.55	0.41
	(0.51)	(1.23)	(0.60)
Forecasts	0.95	0.96	0.97
	(0.05)	(0.12)	(0.06)
Revisions	1.05		
	(0.09)		
Wald Stat.	17.30**	0.96	3.17
Adjusted R^2	0.92	0.44	0.92

[a.] This table shows the results of the PT evaluation in Equation (4) and the FW evaluation in Equation (6).
[b.] As for the note in Table 1.

Table 2: PT and FW Evaluations of Revenue Projections (1960–2020)

	Random Walk	AR(1)	MZ-Adjusted	Vector-MZ-Adjusted
Recursive				
Forecasts	1.07	1.07	0.90**	0.91**
Nowcasts	2.57	2.58	1.02	1.04
Rolling with Window of 30 Years				
Forecasts	1.07	1.11	0.93**	0.94**
Nowcasts	2.57	2.67	1.06	1.16

[a.] This table shows the out-of-sample RMSEs relative to the original revenue projections. We use the first 31 years as a training period to compare the forecast accuracy in the next 30 years.
[b.] ** denotes the significance level at 1 percent based on Clark and West (2007).

Table 3: Comparison of Out-of-Sample RMSEs

Series	Income Tax	Corporate Tax	Consumption Tax
Panel A: Forecasts			
Estimates:			
Constant	0.00	0.01	0.00
	(0.00)	(0.00)	(0.00)
Forecasts	0.87	0.69**	0.99
	(0.12)	(0.13)	(0.03)
Wald Statistic	1.84	5.89*	1.54
Adjusted R^2	0.80	0.68	0.99
Panel B: Nowcasts			
Estimates:			
Constant	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)
Forecasts	1.01	0.85**	1.04*
	(0.06)	(0.05)	(0.02)
Wald Statistic	4.18	8.35*	4.08
Adjusted R^2	0.97	0.92	0.99

[a.] This table shows the results of the MZ forecast evaluation in Equation (3) for the disaggregated series of revenue projections.

[b.] Heteroscedasticity and autocorrelation robust (HAC) standard errors are listed in parentheses. * and ** denote the significance at the level of 5 percent and 1 percent, respectively.

Table 4: MZ Evaluations of Disaggregated Revenue Projections (1989–2020)

	Forecasts		Nowcasts	
	$p = 1$	$p = 2$	$p = 1$	$p = 2$
Panel A: Constant and Past Forecast Errors				
Estimate	0.28**	0.24**	0.29**	0.38
	(0.06)	(0.08)	(0.05)	(0.08)
J-Statistic	3.62	4.73*	2.39	3.43
Panel B: Constant and Past Forecasts				
Estimate	0.27**	0.30**	0.29**	0.21**
	(0.05)	(0.08)	(0.05)	(0.06)
J-Statistic	3.22	3.69	0.35	1.87
Panel C: Constant, Past Forecasts, and Forecast Errors for Growth				
Estimate	0.28**	0.30**	0.29**	0.16**
	(0.05)	(0.08)	(0.05)	(0.06)
J-Statistic	3.24	3.71	1.61	4.70*

[a] This table shows the estimates of alpha in Equation (10) with different sets of instruments.

[b] The test is based on the null hypothesis of $\alpha = 0.5$. Inference is based on HAC standard errors. * and ** denote the significance at the level of 5 percent and 1 percent, respectively.

Table 5: Estimates of Asymmetric Loss Function