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Correcting the January optimism effect

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Abstract

Each month, various professional forecasters give forecasts for next year's real gross domestic product (GDP) growth and unemployment. January is a special month, when the forecast horizon moves to the following calendar year. Instead of deleting the January data when analyzing forecast updates, I propose a periodic version of a test regression for weak-form efficiency. An application of this periodic model for many forecasts across a range of countries shows that in January GDP forecast updates are positive, whereas the forecast updates for unemployment are negative. I document that this January optimism about the new calendar year is detrimental to forecast accuracy. To empirically analyze Okun's law, I also propose a periodic test regression, and its application provides more support for this law.

KEYWORDS

forecast updates, January effect, Okun's law, periodic regression model, weak-form efficiency

1 | INTRODUCTION

Professional forecasters, like those in the Survey of Professional Forecasters¹ and the Consensus Forecasters,² can quote forecasts in each month of the year. Important variables, for which these forecasts are given, are real gross domestic product (GDP) growth and unemployment. The forecast targets are usually yearly real GDP growth and unemployment, where the years are the current year and the following year. For example, in January 2019, forecasts are given for the years 2019 and 2020. Often, the focus is on the average forecast ("consensus"; see, among many others, Ager, Kappler, & Osterloh, 2009; Ashiya, 2003, 2006; Cho, 2002; Dovern & Weisser, 2011; Isiklar, Lahiri, & Loungani, 2006). There are also many studies that include measures of dispersion (see,

among others, Capistran & Timmermann, 2009; Lahiri & Sheng, 2008; Legerstee & Franses, 2015; Manzan, 2011).

The month January each year can be viewed as a special month.³ It is the first month for which the forecast horizon switches to a new year. Whereas the other months concern the forecasts for years T and $T + 1$, in January for the first time, this changes from $T + 1$ to $T + 2$. Strictly speaking, the quote in January does not

¹<https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/>

²<https://www.consensuseconomics.com/>

³This also holds for variables like consumer confidence and stock returns. Ciccone (2011, table 1) reports that consumer confidence generally peaks in January, even though the survey questions ask respondents to think about comparing the next year with this year. Furthermore, there is evidence that stock returns can show a so-called January effect, which is called investor optimism, and which entails that stock returns can be higher on average in January than in other months (see, e.g., Chen & Daves, 2018; Ciccone, 2011). There is a large body of research on optimism or pessimism bias in economic forecasts (see, among many more, Batchelor, 2007). In the present study I do not focus on explaining or analyzing any bias, but I merely focus on correcting for it when studying efficiency and Okun's law.

amount to a forecast revision because the forecast horizon changes, so it is better labeled the “January update.”

In the current study, I examine the forecasts created by professional forecasters to see whether a January effect exists for their forecasts when testing for weak-form efficiency and Okun's law. The data concern the forecasts presented by Consensus Economics and concern real GDP growth and unemployment for various countries.

The outline of this paper is as follows. In Section 2 I put forward the auxiliary regression model that will be used for the analysis of the monthly data. This regression model was introduced by Nordhaus (1987) to examine weak-form efficiency of forecasts, and here it is applied to the monthly updates of forecasts for real GDP growth and unemployment for 13 countries. The first impression is that weak-form efficiency cannot be rejected. In Section 3 I address the impact of January. When the observations on January are deleted, I show that weak-form efficiency must be rejected. Next, I propose a periodic version of the Nordhaus regression, where parameters vary across the months. I document that all real GDP growth forecasts for a new calendar year are raised upwards. Next, I examine a potential January effect for unemployment forecasts for which I document a downward tendency in January. An analysis of forecast accuracy shows that forecast errors are substantially larger in January. Section 4 deals with Okun's law, and with a periodic version of the test regression for this law, I examine whether the January effect has an impact on empirical findings. Section 5 contains the main conclusions.

2 | THE NORDHAUS REGRESSION

The regression model that is often used to examine weak-form efficiency was introduced in Nordhaus (1987). Weak-form efficiency implies that the correlation between subsequent forecast revisions, for the same forecast target, is zero. This means that there is no information in past forecasts that can help to predict future forecast updates. The Nordhaus regression for forecast updates is

$$\text{Update}_t = \alpha + \beta \text{Update}_{t-1} + \varepsilon_t. \quad (1)$$

Under weak-form efficiency it should be the case that $\beta = 0$ in Equation (1).

In this paper I analyze the forecast revisions of the average forecasts (consensus) created by Consensus Forecasters. Each year, there is an average forecast produced in month m in year T for the outcome of an economic

variable in year $T + 1$. Two key variables are real GDP growth and unemployment. The forecasts are $F_{T+1 | T, m}$, where m ranges from January to December. The data in this paper concern the forecasts for 13 countries (or areas) for the period 1995.01–2018.12. For some countries the sample starts later (see Table 1).

For the months February to December the forecast updates are given by

$$F_{T+1|T,m} - F_{T+1|T,m-1} \text{ for } m = \text{February, March, ..., December.}$$

For January, the forecast “updates” are

$$F_{T+2|T+1,\text{January}} - F_{T+1|T,\text{December}},$$

which shows that the “January update” involves a new forecast horizon; that is, year $T + 2$, and this makes January a special month. A graph of the forecast updates for real GDP growth in the USA is given in Figure 1, and there are clear spikes in January. Even though January concerns the focus to a new calendar year, there is no systematic and specific news that makes each new year special.

In Table 1, I present the estimation results for the Nordhaus regression in Equation (1) for the updates in forecasts for real GDP growth for USA, Japan, Germany, France, UK, Italy, Canada, Eurozone, Netherlands, Norway, Spain, Sweden, and Switzerland. The table presents the heteroskedasticity and autocorrelation consistent (HAC) standard errors in parentheses. The R^2 in the final columns in all tables is the adjusted R^2 . The final row gives the estimate for β when the equations are included in an (unbalanced) panel regression where the intercepts vary across countries.

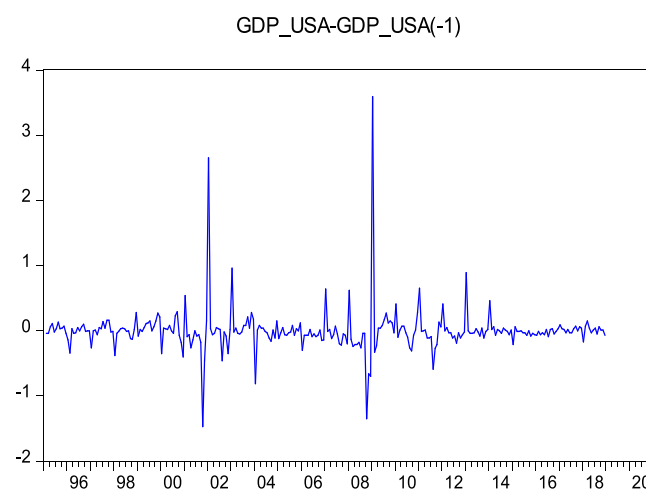


FIGURE 1 Forecast updates, real GDP growth USA, February 1995 to December 2018 [Colour figure can be viewed at wileyonlinelibrary.com]

Clearly, all 13 β parameters are statistically insignificant. When included in a panel model, this parameter is again equal to 0. In other words, weak-form efficiency cannot be rejected.

3 | JANUARY

Given the visual impression from Figure 1, I run the 13 Nordhaus regressions in Equation (1), where now the January observations are not included. The estimation results appear in Table 2. I note that for nine of the 13 countries the β parameter is significantly different from 0, and therefore I now reject weak-form efficiency.

To examine the case of January even further, I convert the Nordhaus regression in Equation (1) into a version where the parameters vary across January and the other months. Denote two seasonal dummy variables $D_{\text{January},t}$ and $D_{\text{February},t}$, which take a value 1 in the months January and February, respectively, and 0 otherwise. A useful periodic Nordhaus regression is

$$\begin{aligned} \text{Update}_t = & \alpha + \alpha_1 D_{\text{January},t} + \beta \text{Update}_{t-1} \\ & + \beta_1 D_{\text{January},t} \text{Update}_{t-1} \\ & + \beta_2 D_{\text{February},t} \text{Update}_{t-1} + \varepsilon_t. \end{aligned} \quad (2)$$

Parameter α_1 provides an additional intercept term for January; β_1 and β_2 make the dynamic structure in the

model different for January and February. The parameters can again be estimated using least squares. Franses

TABLE 2 Estimates of the Nordhaus regression in (1) for forecast updates on real GDP growth (with HAC standard errors in parentheses). Sample size is in Table 1. Data on all January months are excluded. Boldface indicates significance at the 5% level. The R^2 in the final column is the adjusted R^2 . The final row gives the estimate for β when the equations are included in an (unbalanced) panel regression where the intercepts vary across countries

Country/region	α	β	R^2
USA	-0.033 (0.016)	0.078 (0.059)	0.020
Japan	-0.031 (0.015)	0.139 (0.069)	0.031
Germany	-0.034 (0.013)	0.213 (0.065)	0.131
France	-0.039 (0.011)	0.166 (0.063)	0.068
UK	-0.026 (0.013)	0.148 (0.064)	0.053
Italy	-0.050 (0.011)	0.136 (0.047)	0.056
Canada	-0.033 (0.011)	0.131 (0.055)	0.068
Eurozone	-0.035 (0.015)	0.208 (0.094)	0.111
Netherlands	-0.032 (0.014)	0.150 (0.056)	0.052
Norway	-0.018 (0.016)	0.085 (0.053)	0.009
Spain	-0.032 (0.014)	0.098 (0.053)	0.028
Sweden	-0.012 (0.013)	0.183 (0.076)	0.074
Switzerland	-0.025 (0.013)	0.119 (0.078)	0.023
Panel		0.135 (0.010)	

TABLE 1 Estimates of the Nordhaus regression in Equation (1) for forecast updates on real GDP growth (with HAC standard errors in parentheses)

Country/region	Sample	α	β	R^2
USA	1995.01–2018.12	0.001 (0.016)	-0.003 (0.089)	-0.004
Japan	1995.01–2018.12	-0.008 (0.017)	0.002 (0.100)	-0.004
Germany	1995.01–2018.12	-0.004 (0.013)	-0.011 (0.073)	-0.003
France	1995.01–2018.12	-0.005 (0.011)	-0.007 (0.068)	-0.003
UK	1995.01–2018.12	-0.004 (0.013)	0.026 (0.066)	-0.003
Italy	1995.01–2018.12	-0.007 (0.013)	-0.018 (0.068)	-0.003
Canada	1995.01–2018.12	-0.004 (0.012)	0.027 (0.052)	-0.003
Eurozone	2003.01–2018.12	-0.004 (0.015)	-0.017 (0.112)	-0.005
Netherlands	1995.01–2018.12	-0.003 (0.014)	-0.005 (0.067)	-0.003
Norway	1999.01–2018.12	0.005 (0.015)	-0.185 (0.120)	0.030
Spain	1995.01–2018.12	-0.004 (0.016)	-0.013 (0.072)	-0.003
Sweden	1995.01–2018.12	-0.002 (0.012)	0.025 (0.095)	-0.003
Switzerland	1999.01–2018.12	-0.001 (0.012)	0.046 (0.072)	-0.002
Panel			-0.009 (0.017)	

R^2 in the final column is the adjusted R^2 . The final row gives the estimate for β when the equations are included in an (unbalanced) panel regression where the intercepts vary across countries.

and Paap (2004) provide a concise account of periodic time series models.

In Table 3 I present the parameter estimates for Equation (2). If there is an optimistic January effect, I expect α_1 to be positive. When β is positive, there is a tendency

TABLE 3 Estimates of the periodic Nordhaus regression for forecast updates on real GDP growth (with HAC standard errors in parentheses)

Country/region	α	α_1	β	β_1	β_2	R^2
USA	-0.016 (0.010)	0.403 (0.170)	0.475 (0.068)	-3.043 (1.193)	-0.520 (0.088)	0.355
Japan	-0.022 (0.013)	0.210 (0.099)	0.340 (0.092)	-1.425 (0.476)	-0.374 (0.130)	0.238
Germany	-0.014 (0.006)	0.171 (0.074)	0.783 (0.106)	-2.882 (0.323)	-0.770 (0.109)	0.646
France	-0.019 (0.006)	0.296 (0.069)	0.587 (0.113)	-1.926 (0.403)	-0.625 (0.117)	0.521
UK	-0.015 (0.009)	0.137 (0.102)	0.472 (0.189)	-3.002 (0.688)	-0.502 (0.189)	0.408
Italy	-0.029 (0.008)	0.404 (0.087)	0.510 (0.111)	-1.883 (0.358)	-0.514 (0.126)	0.537
Canada	-0.019 (0.007)	0.138 (0.110)	0.526 (0.106)	-3.678 (0.942)	-0.509 (0.099)	0.419
Eurozone	-0.008 (0.006)	0.303 (0.036)	0.833 (0.118)	-2.671 (0.252)	-0.873 (0.127)	0.737
Netherlands	-0.020 (0.010)	0.258 (0.095)	0.434 (0.093)	-2.227 (0.261)	-0.435 (0.096)	0.428
Norway	-0.013 (0.013)	0.125 (0.095)	0.339 (0.111)	-1.629 (0.152)	-0.381 (0.113)	0.385
Spain	-0.015 (0.018)	0.247 (0.138)	0.558 (0.126)	-1.977 (0.474)	-0.611 (0.141)	0.313
Sweden	-0.007 (0.008)	0.045 (0.097)	0.558 (0.146)	-2.260 (0.327)	-0.571 (0.155)	0.341
Switzerland	-0.017 (0.010)	0.346 (0.091)	0.299 (0.169)	-1.422 (0.407)	-0.325 (0.146)	0.279
Panel		0.234 (0.013)				
			0.487 (0.025)			
				-2.169 (0.057)		
					-0.521 (0.030)	
		0.244 (0.012)	0.491 (0.025)	-2.113 (0.056)	-0.514 (0.031)	

Note. Sample size is as in Table 1. Boldface indicates significance at the 5% level. R^2 in the final column is the adjusted R^2 . The final rows give the estimates for α_1 , β , β_1 , β_2 when the equations are included in an (unbalanced) panel regression where the intercepts vary across countries.

TABLE 4 Estimates of the periodic Nordhaus regression for forecast updates on unemployment rate (with HAC standard errors in parentheses)

Country/region	α	α_1	β	β_1	β_2	R^2
USA	0.006 (0.007)	-0.156 (0.067)	0.519 (0.058)	0.907 (0.507)	-0.255 (0.094)	0.309
Japan	0.003 (0.006)	-0.070 (0.039)	0.355 (0.073)	0.583 (0.452)	-0.236 (0.086)	0.171
Germany	0.004 (0.006)	-0.211 (0.062)	0.663 (0.069)	0.312 (0.551)	-0.518 (0.097)	0.371
France	0.007 (0.008)	-0.260 (0.041)	0.514 (0.061)	0.324 (0.259)	-0.430 (0.065)	0.363
UK	-0.015 (0.013)	0.089 (0.093)	0.099 (0.096)	2.187 (1.235)	0.058 (0.107)	0.083
Italy	0.014 (0.009)	-0.237 (0.045)	0.370 (0.074)	0.763 (0.407)	-0.158 (0.079)	0.282
Canada	0.006 (0.007)	-0.206 (0.047)	0.415 (0.077)	0.354 (0.597)	-0.211 (0.103)	0.319
Eurozone	0.009 (0.007)	-0.199 (0.037)	0.698 (0.055)	1.039 (0.039)	-0.367 (0.100)	0.611
Panel		-0.153 (0.011)				
			0.361 (0.024)			
				0.775 (0.095)		
					-0.216 (0.040)	
		-0.160 (0.011)	0.364 (0.025)	0.740 (0.096)	-0.182 (0.040)	

Note. Sample size is as in Table 1. Boldface indicates significance at the 5% level. R^2 in the final column is the adjusted R^2 . The final rows give the estimates for α_1 , β , β_1 , β_2 when the equations are included in an (unbalanced) panel regression where the intercepts vary across countries.

to return to the mean in all months also in January, but when there is an upswing in January I expect β_1 to be negative. When this January upswing is corrected in February, I expect β_2 to be negative too. The estimation results in Table 3 confirm these expectations. For all 13 countries, the estimated β_1 is significant and negative (-2.169 in the panel version of the periodic model), and for all 13 countries β_2 is significant and negative (on average, -0.521). Most α_1 parameters are significant and positive (on average, 0.244). This all suggests that professional forecasters are optimistic in January about the next year to come.

If an optimistic January effect exists, then I expect similar results for a variable like unemployment, where now the sign of α_1 is expected to be negative, and the sign of β_1 is expected to be positive, assuming a positive value for β . The estimation results for eight countries with available forecasts in Table 4 confirm the expectations, with most evidence in the panel version.

Finally, I examine how a January effect translates to forecast accuracy. I take the currently (June 2019) available realizations of real GDP growth (see Figure 2 for the USA) and unemployment rates. In Tables 5 and 6, I present the regression results for the auxiliary regression

$$\text{Absolute forecast error}_t = \alpha + \beta D_{\text{January},t} + u_t, \quad (3)$$

with

$$u_t = \rho u_{t-1} + \varepsilon_t,$$

for real GDP growth and unemployment, respectively.

As can be seen from the relevant column in Table 5, most estimated β parameters for real GDP growth in

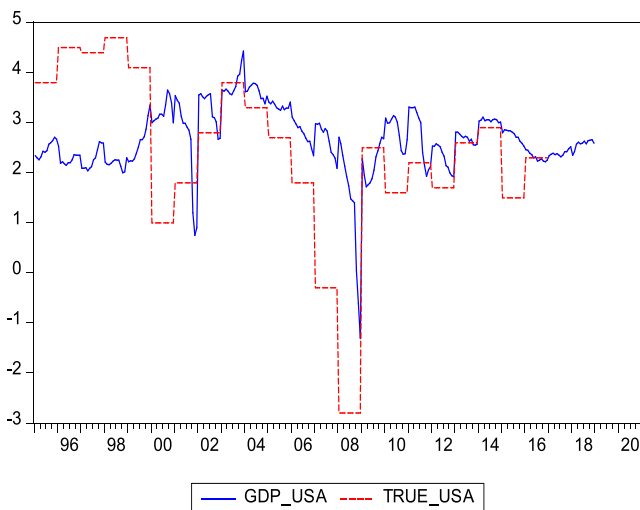


FIGURE 2 Forecasts for real GDP growth, USA (GDP_USA), and realizations (TRUE_USA) (available in June 2019) [Colour figure can be viewed at wileyonlinelibrary.com]

TABLE 5 Absolute forecast errors for real GDP growth, analyzed using the regression model in Equation (3) (standard errors are in parentheses)

Country/region	α	β	% increase absolute error
USA	1.153 (0.720)	0.220 (0.044)	19.1%
Japan	1.324 (0.918)	0.157 (0.072)	11.9%
Germany	1.386 (1.242)	0.266 (0.086)	19.2%
France	0.952 (0.595)	0.140 (0.044)	14.7%
UK	0.822 (0.979)	0.095 (0.061)	11.5%
Italy	1.259 (1.231)	0.197 (0.084)	15.6%
Canada	1.162 (0.903)	0.080 (0.065)	6.9%
Eurozone	1.091 (1.071)	0.259 (0.085)	23.7%
Netherlands	1.388 (0.607)	0.263 (0.062)	19.0%
Norway	1.083 (0.631)	0.077 (0.046)	7.1%
Spain	1.194 (0.801)	0.268 (0.058)	22.5%
Sweden	1.444 (1.744)	0.185 (0.088)	12.8%
Switzerland	1.259 (0.683)	0.118 (0.064)	9.4%
Average			14.9%

Note. Realizations are taken as the currently available value. Boldface indicates significant at the 5% level.

Equation (3) are significant at the 5% level. I conclude that January optimism harms forecast quality. The last column of Table 5 shows that forecasts deteriorate by about 15%, on average. Table 6 shows that such a deterioration of forecast accuracy for unemployment is even about 24%.

In Figure 3, I present the recursive estimates of β in Equation (3), where each time a year with 12 monthly observations is added. Clearly, there is no obvious tendency of the estimated parameter to get smaller over time. In other words, forecasters have not learnt that the January effect is detrimental to forecast accuracy.

4 | OKUN'S LAW

Recent literature on the analysis of professional forecasters has also addressed whether their forecasts reflect Okun's law. This law predicts that there is a negative relationship between real GDP growth forecasts and changes in unemployment rate forecasts (see, e.g., Mitchell & Pearce, 2010; Pierdzioch, Ruelke, & Stadtmann, 2011). It might be that the January effect can also have implications for the consistency of the forecasts with Okun's law. To examine this, I consider the periodic version of the typical regression:

TABLE 6 Absolute forecast errors for unemployment, analyzed using the regression model in Equation (3) (standard errors are in parentheses)

Country/region	α	β	% increase absolute error
USA	0.547 (0.335)	0.237 (0.038)	43.3%
Japan	0.348 (0.110)	0.128 (0.018)	36.8%
Germany	1.290 (0.488)	0.128 (0.022)	9.9%
France	0.624 (0.164)	0.047 (0.017)	7.5%
UK	1.482 (0.673)	-0.046 (0.034)	-3.1%
Italy	0.679 (0.282)	0.215 (0.025)	31.7%
Canada	0.450 (0.188)	0.126 (0.022)	28.0%
Eurozone	0.664 (0.298)	0.263 (0.033)	39.6%
Average			24.2%

Note. Realizations are taken as the currently available value. Boldface β indicates significance at the 5% level.

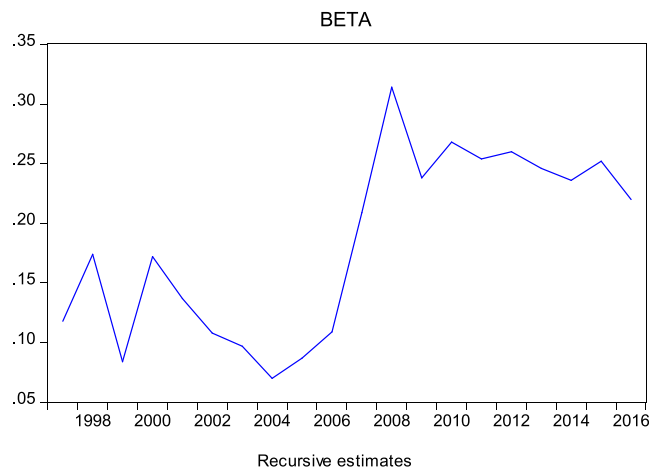


FIGURE 3 Recursive estimates of β in Equation (3) [Colour figure can be viewed at wileyonlinelibrary.com]

$$\begin{aligned} \text{Forecast GDP growth}_t &= \gamma + \gamma_1 D_{\text{January},t} \\ &+ \delta \text{Forecast change in unemployment}_t \\ &+ \delta_1 D_{\text{January},t} \\ &\text{Forecast change in unemployment}_t + u_t. \end{aligned} \tag{4}$$

with $u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \varepsilon_t$. In Table 7 I report the estimation results for δ and δ_1 in Equation (4). The last column of Table 7 shows that, when $\gamma_1 = \delta_1 = 0$, the parameter δ is estimated to be equal to -0.709 , on average, for eight countries. When I correct for the January effect, the average parameter δ is estimated as -0.767 , which is due to an upward effect of January, on average equal to 0.194. Table 7 shows that this January effect is significant for five of the eight countries. Finally, when I consider the full model, I conclude that all eight δ parameters are statistically significant.

TABLE 7 Testing Okun's law: estimation results for δ and δ_1 in the test regression

Country/region	Based on full model		Model with $\gamma_1 = \delta_1 = 0$
	δ	δ_1	δ
USA	-1.126 (0.023)	0.240 (0.062)	-1.072 (0.019)
Japan	-1.249 (0.061)	0.303 (0.082)	-1.178 (0.057)
Germany	-0.263 (0.034)	0.080 (0.045)	-0.209 (0.029)
France	-0.632 (0.024)	0.020 (0.025)	-0.668 (0.025)
UK	-0.258 (0.025)	-0.001 (0.026)	-0.209 (0.026)
Italy	-0.536 (0.037)	0.170 (0.045)	-0.493 (0.035)
Canada	-1.283 (0.034)	0.635 (0.048)	-1.041 (0.025)
Eurozone	-0.792 (0.022)	0.103 (0.051)	-0.798 (0.025)
Average	-0.767	0.194	-0.709

Note.

Forecast GDP growth_t = $\gamma + \gamma_1 D_{\text{January},t} + \delta$ Forecast change in unemployment_t + $\delta_1 D_{\text{January},t}$ Forecast change in unemployment_t + u_t , with $u_t = \rho_1 u_{t-1} + \rho_2 u_{t-2} + \varepsilon_t$. Boldface indicates significance at the 5% level.

5 | CONCLUSION

In this paper I proposed modified test regressions for efficiency and Okun's law to take care of the January effect. These test regressions include periodically varying parameters. An application of a periodic model for weak-form efficiency of forecast updates across a range of countries showed that, in January, GDP forecast updates are positive and the forecast updates for unemployment are negative. Additionally, I documented that the January optimism about the new calendar year is detrimental to forecast accuracy. An application of a periodic version of the test regression for Okun's law resulted in stronger empirical evidence for this law.

The main conclusion of this paper is that I recommend taking explicit account of the January effect when analyzing forecasts from professional forecasters, preferably using a periodic version of test regressions. Further research can concern the analysis of variables other than GDP and unemployment and the forecasts of forecasters other than those in Consensus Forecasts.

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DATA AVAILABILITY STATEMENT

The data are available from the author upon request.

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