Polish GDP Forecast Errors: A Tale of Ineffectiveness

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Abstract

The aim of this paper is to evaluate gross domestic product (GDP) forecast errors of Polish professional forecasters based on the individual data from the *Rzeczpospolita* daily newspaper. This dataset contains predictions on forecasting competitions during the years 2013–2019 in Poland. Our analysis shows a lack of statistical effectiveness of these predictions. First, there is a systemic negative bias, which is especially strong during the years of conservative PiS government rule. Second, the forecasters failed to correctly predict the effects of major changes in fiscal policy. Third, there is evidence of strategic behaviors; for example, the forecasters tended to revise their prognosis too frequently and too excessively. We also document herding behavior, i.e., an alignment of the most extreme forecasts towards market consensus with time, and an overly strong reliance on forecasts from NBP inflation projections in cases of estimates for longer horizons.

Keywords: GDP forecasting

JEL classification codes: E32, E37

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1. Introduction

The aim of this paper is to evaluate gross domestic product (GDP) forecast errors of Polish professional forecasters based on individual-level data from the *Rzeczpospolita* daily newspaper. The dataset contains predictions from forecasting competition and covers the years 2013 to 2019. Based on statistical tests, we analyze the unbiasedness and effectiveness of the forecasts, as well as potential irregularities in the process of forecast revisions and consensus formation.

We identified the following problems:

1) The systematic underestimation of growth dynamics, particularly visible during the years 2016 to 2019, i.e. in the time of conservative PiS government rule.
2) An inability to correctly forecast the effects of changes related to fiscal policy or structural reforms. Professional forecasters significantly underestimated the consequences of transition to new EU budget perspective, which resulted in contraction of investments growth. They probably also overestimated the effects of the introduction of a child benefit. These errors resulted in the forecast revisions of greatest magnitude and the biggest surprises in the analyzed sample.
3) Excessive and overly frequent revisions of activity forecasts. A strong revision in quarter t tends to be reversed in the next quarter ($t+1$). Similar to the forecast errors, revisions are more likely to be positive rather than negative, especially after 2016.
4) Evidence of strategic behaviors. Two forecasters tended to more strictly follow market consensus rather than produce controversial estimates. There was also a tendency to align the most extreme forecasts toward a market consensus; this is known as a herding behavior. Finally, any disagreement tends to be lower for the forecast with longer time horizon. This phenomenon suggests that forecasters are anchoring their expectations closely on the official projection of the central bank.

Most of these problems are also reported in the G10 economies. However, we highlight two solutions which may limit the ineffectiveness of forecasts. First, in Poland, the market for economic forecasts is dominated by the commercial banks—90% of the forecasts are produced by representatives of those entities. Greater participation of public sector entities, i.e., the Ministry of Finance, the Ministry of Economy, the National Bank of Poland (NBP), and the Polish Economic Institute, may be beneficial. Second, there are no systemic incentives for the academic sector to shape the public debate and regularly present economic forecasts. Modelling competitions organized by public sector entities may help to activate this group.

This manuscript is structured as follows. Section 2 provides a literature review on GDP forecasting, describing irregularities visible especially in the G7 space. Section 3 delivers information about the dataset. Section 4 summarizes the methodology. Section 5 discusses the results of the estimation. Finally, section 6 concludes the paper.

2. Literature Review

The aim of this section is to present problems related to GDP growth forecasting reported previously in the academic literature. The prediction of a business cycle is probably one of the most sophisticated exercises done by economists and forecast errors are usually greater compared to other economic figures such as inflation (Lahiri & Sheng 2010; Loungani et al., 2013). Furthermore, researchers report persistent systematic biases which are especially visible in the forecasts with longer horizons (Ager et al., 2009). There is also strong evidence of failure to predict severe downturns (Loungani, 2001) or effects of structural changes, e.g., those related to fiscal policy (Blanchard & Leigh, 2013).

The Polish economic debate is particularly driven by commercial economists representing the banking sector. The literature on the subject highlights a few significant problems related to such situations.

First, the primary aim of such forecasters is not necessarily to minimize forecast errors, but rather to realize some other strategic objectives, for example, a greater presence in the media or triggering some policy actions (Pons-Novell, 2003; Dovern & Weisser, 2011). This may result in two opposite phenomena: either strong and systematic deviations from the market consensus or self-censorship to avoid such discrepancies (i.e. herding behavior). Some authors (e.g., Ashiya, 2009) claim that forecasting may reflect the interests of the forecaster employer – for example representants of banking sectors in some periods may be more pessimistic than academics and the difference between estimates is statistically significant.

Second, there is a widespread debate about irregularities visible in the revisions of the forecasts done by professionals. In a perfect world, the pattern of the revisions would be totally unpredictable and follow a random walk process (Nordhaus, 1987) however, this is not always the case. Several studies operating on monthly data show that forecasts are too rigid and too sluggish in incorporating incoming information (Lahiri & Sheng, 2010; Loungani et al., 2013; Capistrán & López-Moctezuma, 2014). There are also reports providing examples of strategic behaviors such as presenting overly optimistic or pessimistic estimates in order to acquire publicity (Ashiya, 2003). Finally, forecast revisions sometimes may be used to trigger significant policy actions or affect valuation in a financial instrument. However, these effects are rather more frequently seen in cases of publicly listed companies' earnings announcements (e.g., Gleason & Lee, 2003; Kasznik & McNichols, 2002), rather than in relation to macroeconomic variables.

Finally, several papers suggest there is an interaction between public and private sector forecasts. Behavioral economists suggest the effect of an anchoring bias (Campbell & Sharpe, 2009); there is also evidence that the establishment of public forecasts may crowd out some efforts from the private sector (Tong, 2007).

We propose three different statistical tests to identify if forecasts are unbiased and free of strategic behaviors. The detailed information will be presented in the methodology section.

3. The *Rzeczpospolita* Forecasting Competition

This section describes the dataset used in this study. The *Rzeczpospolita* competition was established in 2008 by NBP Governor Sławomir Skrzypek to promote better macroeconomic forecasting. The competition initially contained five categories of forecasts: gross domestic product (GDP), gross fixed capital formation (GFCF), Consumer Price Index (CPI), unemployment rate, and the current account of the balance of payments. The NBP abandoned supporting the competition in 2015. After this event, Rzeczpospolia modified the forecast variables: private consumption and exchange rate forecasts were added; there was no further interest in forecasting the current account of the balance of payments or unemployment rate.

The *Rzeczpospolita* survey is conducted quarterly. Polled analysts provide their estimates for the four quarters ahead. For example, at the end of September, analysts provide their estimates for the last quarter of the survey year and the first, second, and third quarters of the following year. At the time of the survey, information regarding GDP dynamics in the current quarter is still unavailable, and the analysts must base their estimates on monthly data (e.g., industrial production and construction output). In December, the window moves by one quarter, and at that time, the surveyed analysts are unaware of the GDP reading for the current quarter, and so on.

The dataset used for this study consist of the individual forecasts covering the period from 2013 to 2019. We excluded the participants who posted their estimates irregularly or belonged to student associations (due to frequent rotations of the forecasters). Therefore, we were left with forecasts from 20 permanent contributors: 90% of them representing financial institutions and 10% representing academic institutions or think tanks.

4. Methodology

This section presents the methodology of our research. Our aim was to analyze the effectiveness of the GDP forecasts for the Polish economy based on two independent tests. We also verify whether there is evidence of strategic behaviors by the forecasters, following the approach of Pons-Novell (2003).

Below, we define the key variables used in the analysis:

GDP_t denotes the annual dynamics of gross domestic product in the quarter t.

$GDP_{t,h}^{f_i}$ represents the i-th professional forecaster's prognosis of gross domestic product in the quarter t, formulated h quarters prior to the reading. i takes values from 1 to n, where n denotes the number of forecasters. We will use the superscript f_i every time a variable is related to the forecasts and not to a realized macroeconomic reading.

μ_i stands for the individual error of the i-th professional forecaster, estimated using fixed effects model.

θ_t denotes a time period effect.

ε_t represents a random disturbance.

β_x are estimated parameters.

4.1 Effectiveness of Forecasts: The First Statistical Test

The first test of forecast effectiveness assumes that forecast errors should have no systematic bias. We follow an approach used previously by Ashiya (2003, 2009), Loungani (2001), and Lahiri and Sheng (2010). This test is also widely adopted in different contexts, for example, with fiscal forecasts (Artis & Marcellino, 2001; Brück & Tilman, 2005; Pina & Venes, 2011).

We formulate the following equation using an ordinary linear regression with cross-section and period fixed effects:

$$GDP_t = \beta_0 + \beta_1 * GDP_{t,h}^{f_i} + \mu_i + \theta_t + \varepsilon_t \qquad (1)$$

An effective forecast should meet the following criteria:

(1) There are no systematic biases. Therefore, parameters β_0 and μ_i should both be statistically insignificant for each forecaster.

(2) Forecasts should correctly describe the final realization of GDP, except for some random disturbances related to θ_t and ε_t. This implies that $\beta_1 = 1$.

(3) θ_t is a white noise series.

We assume there is no multiplicative error in the forecast. Therefore, we simplify the first equation and provide the following model:

$$GDP_{t,h}^{f_i} - GDP_t = \beta_0 + \mu_i + \theta_t + \varepsilon_t \tag{2}$$

Our aim is to test and verify the hypotheses presented in criteria (1) and (3).

4.2 Effectiveness of Forecasts: The Second Statistical Test

The second test follows the approach proposed by Nordhaus (1987). We attempt to verify whether the forecast revisions indeed follow a white noise process. Let us denote $REV_{t,h}^{f_i}$ as the magnitude of a forecast revision of GDP in the quarter t, prepared h quarters prior to the reading. The indicators denote the difference between the most recent forecast at the time $(t - h)$ and the previous one, done in the period $(t - h - 1)$. The computation is given by the following formula:

$$REV_{t,h}^{f_i} = GDP_{t,h}^{f_i} - GDP_{t,h-1}^{f_i} \tag{3}$$

We attempt to estimate the following autoregressive model with fixed and period effects:

$$REV_{t,h}^{f_i} = \beta_0 + \beta_1 * REV_{t,h-1}^{f_i} + \mu_i + \theta_t + \varepsilon_t \tag{4}$$

Our aim is to verify the following hypotheses:

(1) A past revision should not give information regarding the forecaster's next decision. If the forecasts are effective, then parameter β_1 is required to be statistically insignificant.

(2) The cross-section fixed effect μ_i should be statistically insignificant.

(3) θ_t should be a white noise series.

We will also verify whether the magnitude of forecast revisions differ substantially between professionals. Some analysts may have a greater propensity to perform stronger revisions and to do so more frequently just to attract greater attention from the media. Therefore, we will compute the absolute values of the magnitudes of the forecast revisions and average them.

4.3 Strategic Behaviors of Forecasters

Finally, based on the approach of Pons-Novell (2003), we attempt to verify whether there exists any evidence of strategic behaviors on the part of the forecasters. This methodology focuses on deviation of individual forecasts from the market consensus. We define the market consensus as the median of available forecasts.

$$Consensus_{t,h}^{f_i} = Median(GDP_{t,h}^{f_1}, GDP_{t,h}^{f_2}, \dots\dots, GDP_{t,h}^{f_n}) \tag{5}$$

Our aim is to analyze deviations from the market consensus, calculated by a simple subtraction.

$$Deviation_{t,h}^{f_i} = GDP_{t,h}^{f_i} - Consensus_{t,h}^{f_i} \tag{6}$$

First, we analyze whether the magnitude of such deviations differs significantly between the forecasters. Forecasters can estimate the value of a market consensus prior to its publication as real-time information is available on the Bloomberg terminal; monthly estimates are also aggregated by a Consensus Economics poll. Therefore, some groups of analysts may have the temptation to self-censor their estimates and not deviate strongly from the median.

To perform this exercise, we calculate the deviations of each forecaster's projections from the consensus using equation 6. Then, we compute the absolute values of those deviations and average them separately for each forecaster. We perform a single *t*-test to verify whether the average deviation produced by a single forecaster is substantially different from those of other professionals. Forecasters strictly following the consensus should have substantially lower deviations, whereas economists lobbying for some policy action would produce greater deviations.

Second, we attempt to identify evidence of herding behavior using the following model:

$$Deviation_{t,h}^{f_i} = \beta_0 + \beta_1 * Deviation_{t,h-1}^{f_i} + \mu_i + \theta_t + \varepsilon_t \tag{7}$$

Values of β_1 lower than 1 suggest that forecasters are prone to correct their deviations and move closer to the consensus values as the forecast horizon shortens and estimates start to gain greater publicity.

5. Estimation Results

In this section, we present and discuss the results of our estimation. We find evidence of strategic behavior, and of both group and individual biases in the forecasts.

5.1 First Test: Analysis of Forecast Errors

The first test confirms the ineffectiveness of professional market forecasts. First, the constant parameter β_0 is negative and statistically significant for all forecast horizons. Forecasts published in the examined window (2013-2019) tend to underestimate GDP growth dynamics by 0.4 to 0.6 percentage points (further pp). Detailed results are presented in Table 1.

Second, based on the statistical tests for redundant cross-section effects, we reject the null hypothesis that parameters corresponding to such effects are statistically insignificant (equal to zero). The problem of individual biases is quite visible in the parameter estimates. One survey respondent tended to systematically present much more pessimistic forecasts as compared to the average derived for other respondents; the discrepancy amounts to another 0.5–0.6pp for the longer horizon (3Q–4Q). The respondent with the second largest negative bias provided forecasts that were lower by 0.2–0.3pp as compared to the average. The estimated cross-section of effects is presented in Table 2.

Finally, the estimated time period effects are not representing a white noise process. There are two episodes confirming problems in forecasting structural changes and downturns. First, analysts overestimated the potential effect of introducing a child benefit program in 2015 and early 2016. Second, they were incapable of predicting the duration of the slowdown related to contraction of investments during transition between EU budget perspectives. There was also a systematic shift in GDP forecasting errors for the years 2016 to 2019. During this time, forecasts were overly negative. This phenomenon may be related to a negative assessment of the economic policies proposed by the PiS government. The period effects are presented in Figure 1.

5.2 Second Test: Analysis of Forecast Revisions

The second test also confirms that forecasts are statistically ineffective. Before analyzing the model output, we should note that the magnitude of revision is different, depending on the time horizon and market participant. Detailed data is presented in Table 3.

The strongest revisions occur in the quarters directly preceding the publication of data. The magnitude of revisions becomes lower, as forecasts horizon increases. There is a group of respondents (i.e. 8, 9, 12, and 16) who tend to revise forecasts more sharply compared to others. There is also a group that make significantly smaller revisions (respondents 14 and 20).

The model confirms existences of autoregressive patterns visible in the data. There is statistically significant evidence that forecasters are prone to making excessively strong changes in their prognosis. A negative parameter of β_1 (-0.3) indicates that a revision made in the previous quarter is usually corrected in the next round of polls. There is also evidence of systematic upward revisions: parameter β_0 is positive in case of both forecast horizons. This evidence confirms the problem of systematic bias observed with the previous test. A detailed description of the model is available in Table 4.

Estimates of cross-fixed effects and period effects are presented in Figures 2 and 3. Similar to the findings with the first test, there is evidence of persistent one-sided revisions during the time of PiS government rule (2017-2019).

5.3 Third Test: Herding Behavior

Finally, we also studied whether there is visible strategic behavior regarding an approach to market consensus. As with the previous test, we start from an analysis of descriptive data shown in Table 5.

First, absolute values of deviation from market consensus and forecast disagreement are greater in the short term. Contrary to intuition and statistics, there is evidence of decaying disagreement with a longer forecast horizon. This problem may be caused by a willingness to follow central bank inflation projections (see e.g., Kotlowski, 2015). However, the NBP does not provide public access to quarterly forecasts; therefore, we are not capable of replicating this research.

Second, the first two participants tended to more frequently formulate forecasts that do not deviate from the current market consensus (indexed as 1 and 2). Simultaneously, one of the pessimistic participants identified in the first test was also much more likely to deviate more strongly than the others from the market consensus in the 3Q–4Q horizon.

The third model, specified in equation 7, confirms the existence of herding behavior. Parameter β_1 is lower than 1 in each time horizon. Alignment toward consensus is most visible during a period of one to three quarters prior to publication. The model's specification is presented in Table 6.

6. Policy Conclusions

The analysis of the Polish macroeconomic forecasts shows all the major imperfections identified in the subject literature, i.e., the existence of systematic biases and problems with correct forecasting of structural and fiscal changes. There is also strong evidence of strategic behaviors, seen in excessively strong forecast revisions and a willingness to align with a market consensus.

The total elimination of the identified problems is probably impossible; however, it is worth considering ways to minimize the influence of dishonest behaviors. There is a discrepancy between the share of professional forecasters from the banking sector in Poland (90%) and G7 (around 50% in the eurozone according to Bowles et al., 2007). A greater diversification of forecasters' backgrounds may be beneficial.

A short-term solution may be provided by a more active engagement of public institutions in the debate in Poland. Presently, the government's forecasts are provided twice per year (around April and October), and the central bank's forecasts are provided three times per year (March, July, and November); more frequent projections and auditing of errors should foster the debate. As mentioned earlier, such decisions also have adverse effects, such as eliminating some private participants (Tong, 2007).

The long-term problem is related to the low activity of academic and non-governmental institutions in these debates. Again, the public sector should provide incentives for greater participation in the public debates, for example, by using granting schemes. Some competition in developing forecasting models may also help to improve the forecasting market.

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Table 1: Test 1 – Bias in Estimated Forecasts

	Forecast horizon			
	1Q ahead forecast	2Q ahead forecast	3Q ahead forecast	4Q ahead forecast
Model Constant	-0.46 (0.01; 0.00***)	-0.52 (0.01; 0.00***)	-0.59 (0.01; 0.00***)	-0.60 (0.01; 0.00***)
R-squared	0.88	0.89	0.90	0.90
Observations	427	408	425	424
Periods	22	21	22	22
Cross-sections	20	20	20	20

This table presents the parameter estimates of β_0 for different forecast horizons. The model specification is presented in equation 2. Negative parameters for the model constant (the second row) denote that GDP forecasts were overly pessimistic in the analyzed period (2013-2019).

Table 2: Test 1 – Estimated Cross-Section Effects

	Estimated fixed effects for different forecast horizons				Standardized values (number of standard deviations from the mean)			
Respondent	1Q ahead forecast	2Q ahead forecast	3Q ahead forecast	4Q ahead forecast	1Q ahead forecast	2Q ahead forecast	3Q ahead forecast	4Q ahead forecast
1	-0.01	0.08	0.07	0.07	-0.15	0.62	0.41	0.33
2	0.02	0.02	0.12	0.16	0.17	0.18	0.66	0.81
3	-0.12	-0.10	-0.05	-0.06	-1.27	-0.77	-0.29	-0.30
4	-0.08	-0.06	-0.02	-0.09	-0.92	-0.41	-0.10	-0.45
5	0.06	0.11	0.03	0.04	0.62	0.82	0.14	0.19
6	0.05	0.02	0.00	0.04	0.57	0.14	-0.03	0.21
7	-0.12	-0.14	-0.10	0.00	-1.28	-1.06	-0.56	0.00
8	-0.11	-0.22	-0.25	-0.26	-1.25	-1.63	-1.39	-1.29
9	0.02	0.09	0.25	0.26	0.21	0.69	1.35	1.30
10	0.18	0.18	0.23	0.27	2.01	1.35	1.26	1.35
11	0.03	0.05	0.03	-0.06	0.32	0.36	0.17	-0.29
12	0.04	0.07	-0.04	-0.01	0.42	0.49	-0.21	-0.03
13	-0.01	0.02	0.02	-0.07	-0.13	0.15	0.12	-0.34
14	-0.03	-0.03	-0.01	-0.01	-0.32	-0.24	-0.06	-0.06
15	0.02	0.06	0.06	0.04	0.17	0.47	0.32	0.19
16	0.02	-0.06	-0.12	-0.04	0.22	-0.45	-0.65	-0.19
17	0.09	0.06	0.13	0.19	1.01	0.43	0.71	0.96
18	-0.04	-0.02	0.04	-0.05	-0.42	-0.17	0.19	-0.24
19	-0.17	-0.36	-0.58	-0.64	-1.84	-2.67	-3.19	-3.21
20	0.17	0.23	0.21	0.21	1.86	1.70	1.14	1.06
Average	0.00	0.00	0.00	0.00				
Std. Dev.	0.09	0.14	0.18	0.20				

This table presents the parameter estimates of μ_i for different forecast horizons (columns 2-5). Columns 6-9 show standardized values. The model specification is presented in equation 2. Respondents 8 and 19 systematically present more negative forecasts compared to other professionals; given that the β_0 values are negative (Table 1), they are more biased than their competitors. Forecasters 10 and 20 are less biased.

Table 3: Test 2 – Magnitude of Revision (pp)

	Magnitude of revisions (absolute value)			Standardized values (Number of standard deviations from the mean)		
Respondent	3Q before publication	2Q before publication	1Q before publication	3Q before publication	2Q before publication	1Q before publication
1	0.21	0.33	0.36	-1.11	0.06	0.17
2	0.30	0.30	0.26	0.66	-0.32	-1.18
3	0.23	0.26	0.45	-0.67	-0.78	1.30
4	0.26	0.38	0.34	-0.10	0.59	-0.12
5	0.26	0.34	0.35	-0.18	0.17	-0.03
6	0.27	0.17	0.30	0.17	-1.71	-0.69
7	0.25	0.25	0.23	-0.32	-0.91	-1.63
8	0.28	0.48	0.47	0.40	1.68	1.62
9	0.31	0.41	0.48	0.97	0.94	1.70
10	0.28	0.30	0.33	0.38	-0.32	-0.26
11	0.24	0.26	0.31	-0.55	-0.80	-0.55
12	0.28	0.51	0.41	0.36	2.02	0.74
13	0.22	0.30	0.34	-0.98	-0.32	-0.16
14	0.18	0.23	0.26	-1.85	-1.04	-1.21
15	0.31	0.36	0.38	1.03	0.31	0.44
16	0.35	0.47	0.38	1.86	1.57	0.44
17	0.32	0.28	0.37	1.21	-0.56	0.32
18	0.30	0.31	0.34	0.84	-0.22	-0.08
19	0.27	0.41	0.44	0.08	0.93	1.17
20	0.16	0.21	0.20	-2.22	-1.28	-1.99
Average	0.26	0.33	0.35			
Std. Dev.	0.05	0.09	0.08			

This table presents the absolute values of forecast revisions (columns 2-4). Columns 5-8 show standardized values. The magnitude of the revisions was calculated with the formula presented in equation 3. Respondents 8,9,12, and 16 tended to make bigger revisions compared to the others; respondents 14 and 20 made smaller revisions.

Table 4: Test 2 – Autoregressive Models of Forecast Revisions

	Horizon	
	1Q ahead revision	2Q ahead revision
Model Constant	0.11 (0.01; 0.00***)	0.05 (0.01; 0.00***)
Previous Revision	-0.32 (0.05; 0.00***)	-0.30 (0.06; 0.00***)
R-squared	0.63	0.58
Observations	438	438
Periods	23	23
Cross-sections	20	20

This table presents the parameter estimates of β_0 and β_1 for different forecast horizons. The model specification is presented in equation 4. Positive values of the model constant β_0 (the second row) confirm that the forecasters were overly pessimistic—the number of positive revisions is greater than the number of negative ones. Negative values of the model constant β_0 after the previous revision (the third row) imply that the forecasters are prone to making overly strong revisions; the changes are often reversed in the next quarter.

Table 5: Test 3 – Average of Absolute Deviations from the Market Consensus

	Average deviation from market consensus (absolute value)				Standardized values (number of standard deviations from the mean)			
Respondent	1Q ahead forecast	2Q ahead forecast	3Q ahead forecast	4Q ahead forecast	1Q ahead forecast	2Q ahead forecast	3Q ahead forecast	4Q ahead forecast
1	0.16	0.15	0.17	0.16	-2.53	-2.72	-2.36	-2.12
2	0.37	0.41	0.29	0.28	-1.58	-1.12	-1.36	-1.06
3	0.56	0.43	0.33	0.34	-0.72	-1.01	-1.04	-0.57
4	0.51	0.46	0.46	0.39	-0.92	-0.79	0.03	-0.12
5	0.52	0.40	0.40	0.34	-0.90	-1.18	-0.46	-0.53
6	0.58	0.51	0.45	0.42	-0.61	-0.50	-0.10	0.15
7	0.74	0.71	0.49	0.34	0.10	0.75	0.28	-0.53
8	0.85	0.89	0.64	0.46	0.62	1.86	1.43	0.52
9	0.79	0.68	0.45	0.44	0.33	0.59	-0.07	0.36
10	0.75	0.60	0.47	0.43	0.15	0.08	0.09	0.29
11	0.86	0.74	0.58	0.52	0.66	0.91	0.95	1.03
12	0.73	0.62	0.37	0.34	0.05	0.17	-0.71	-0.54
13	0.84	0.61	0.44	0.53	0.57	0.13	-0.15	1.10
14	0.87	0.59	0.43	0.37	0.71	0.03	-0.26	-0.28
15	1.07	0.66	0.46	0.35	1.61	0.47	-0.04	-0.40
16	0.98	0.67	0.62	0.42	1.22	0.51	1.28	0.19
17	0.94	0.69	0.56	0.49	1.04	0.63	0.79	0.77
18	0.86	0.74	0.43	0.35	0.67	0.93	-0.21	-0.43
19	0.64	0.59	0.72	0.72	-0.34	0.00	2.07	2.81
20	0.69	0.63	0.44	0.33	-0.12	0.26	-0.17	-0.66
Average	0.71	0.59	0.46	0.40				
Std. Dev.	0.22	0.16	0.12	0.11				

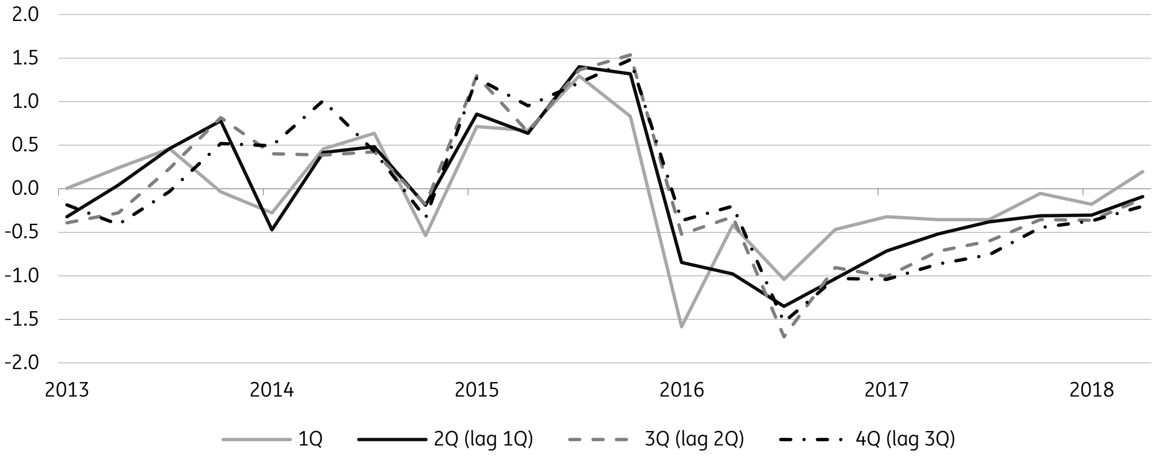
This table presents the absolute values of forecast deviations from the market consensus (columns 2-5). Columns 6-9 show standardized values. Deviations were calculated with the formulae presented in equations 5 and 6. Respondents 1 and 2 tended to strictly follow the consensus. This may be a result of strategic behavior rather than use of independent models.

Table 6: Test 3 – Deviation from Market Consensus

	Forecast horizon			
	1Q ahead forecast	2Q ahead forecast	3Q ahead forecast	4Q ahead forecast
Model Constant	0.48 (0.05, 0.00***)	0.31 (0.04, 0.00***)	0.21 (0.03, 0.00***)	0.19 (0.03, 0.00***)
Deviation in the previous quarter	0.49 (0.07, 0.00***)	0.70 (0.11,0.00***)	0.55 (0.10,0.00***)	
Deviation of the previous forecast				0.19 (0.07,0.01***)
R-squared	0.40	0.44	0.66	0.62
Observations	286	317	381	381
Periods	22	23	25	25
Cross-sections	20	20	20	20

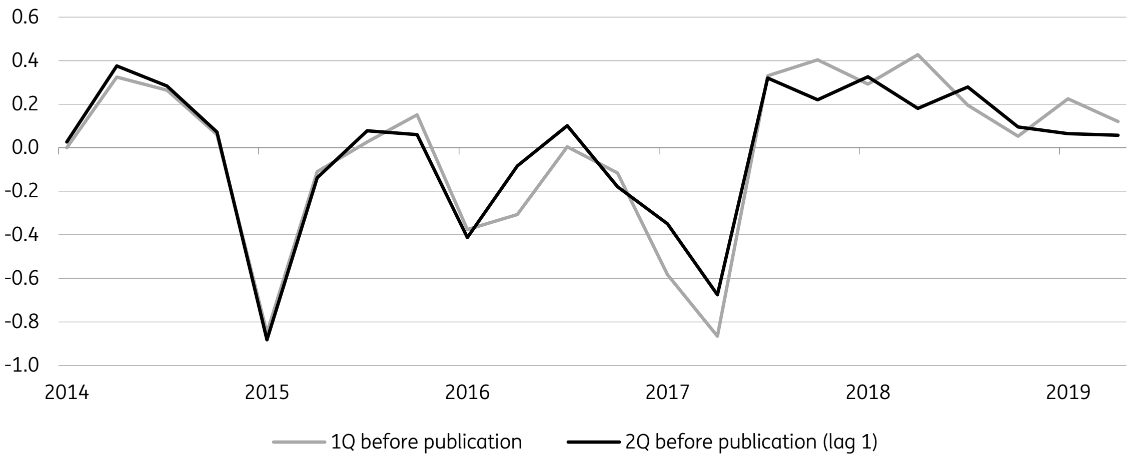
This table presents the parameter estimates of β_0 and β_1 for different forecast horizons. The model specification is presented in equation 7. Values of β_1 lower than 1 (rows 3 and 4) imply that the forecasters are self-censoring to avoid large deviations from the market consensus (herding behavior).

Figure 1: Test 1 – Visualization of Period Effects



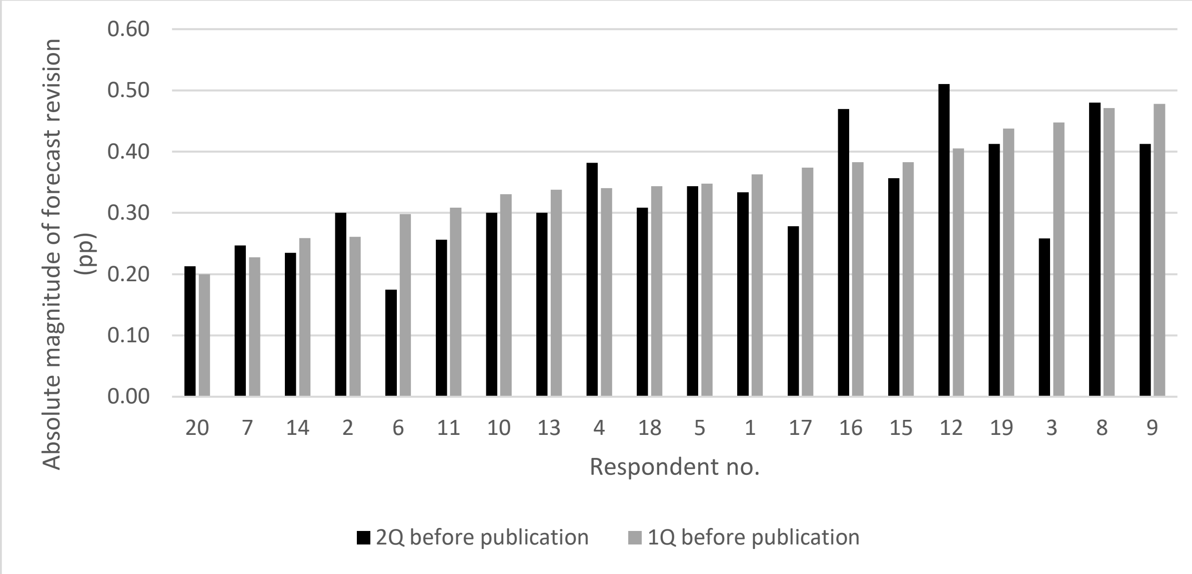
This figure presents the estimated values of θ_t for different forecast horizons. The model specification is presented in equation 2. The lag relationships were used to group the forecasts corresponding to the same poll release. A negative systematic bias persists in the years 2016-2019, during PiS government rule.

Figure 2: Test 2 – Visualization of Period Effects



This figure presents the estimated values of θ_t for different forecast horizons. The model specification is presented in equation 4. The lag relationships were used to group the forecasts corresponding to the same poll release. This series is not an example of a white noise process—we see some persistence of one-sided revision (e.g., during 2017-2019).

Figure 3: Test 2 – Magnitude of Revisions



This figure presents the estimated values of μ_i *for different forecast horizons. The model specification is presented in equation 4. The estimates confirm that some forecasters tend to make overly strong revisions. For greater details, see also Table 3.*