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Macroeconomic forecasting in Poland: lessons from the external shocks

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Abstract

The aim of this paper is to analyse the forecast errors of Polish professional forecasters under the external shock of the COVID-19 crisis in 2020-based on the *Parkiet* competition. This analysis shows that after the initial disruption related to the imposed lockdown in March and April, commercial economists were able to lower their forecasts errors of the industrial production and retail sales. On the other hand, a far worse performance has been seen in the case of the market variable; either the size of errors or the disagreement were elevated throughout the whole of 2020. Furthermore, long--term forecasts that were produced during the first year of the pandemic have been characterized with visible inconsistencies, i.e. forecasts of economic growth were similar when forecasters either assumed a strong increase in unemployment or when they did not. Economists made the biggest error in case of labour market forecasting. This phenomenon is likely related to the scarcity of information in the public statistics. Such problems are likely to repeat in the case of other external shocks, i.e. the forthcoming energy crisis.

Keywords: GDP forecasting, labour market forecasts, COVID-19, forecasts' accuracy, forecasts' consistency

JEL: E27, E32, E37

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1. Introduction

The aim of this paper is to evaluate the forecast errors of Polish professional forecasters during the year 2020 (i.e. in the wake of the COVID-19 pandemic). We would like to verify whether forecasts are free of systemic biases and whether their revisions are consistent with the basic economic theorems. Such an analysis should provide guidance for the policymakers in which areas the forecasts are the most uncertain during the stress periods. So far, a relatively low number of studies provides conclusions; furthermore, they are mainly focused on the forecasts of international institutions, such as the OECD or the IMF (Döpke, Fritsche, Müller 2019; Lewis, Pain 2015). This study is based on a database of individual forecasts from two competitions that are managed by a daily newspaper named *Rzeczpospolita*.

First, we analysed the accuracy of monthly nowcasts, which were based on 12 polls, published from January to December 2020. Nowcast stands for the estimate of the current data release, which was published prior to the official information. Estimates are published by approximately 27 analysts. Second, we analysed four series of one-year projections that were published by 30 economic experts. Analysts provide information about expected GDP growth, their components, and the unemployment rate. We then analyse that information in the context for either unbiasedness or a rationality of revisions.

The monthly polls show that the COVID-19 outbreak resulted in the increase in both industrial production and retail sales forecast errors, which caused a large amount of disagreement for the first three months of the pandemic. After that period, commercial economists were able to reduce errors. On the other hand, economists have a much worse performance in forecasting the conditions of the labour market. Both forecast errors and the disagreement remained elevated for the entire year.

The one-year-ahead forecasts, which were produced during the COVID-19 pandemic, were not statistically efficient. First, revisions were often exaggerated in the wake of lockdowns. Second, labour market errors were one-sided. Furthermore, there are evident inconsistencies between the revisions of macroeconomic variables. Revisions of the labour market forecast have not influenced estimates for Gross Domestic Product (GDP) growth, despite the large scale of changes.

This manuscript is structured as follows. Section 2 provides a literature review on macroeconomic forecasting and irregularities that are visible in Poland. Section 3 provides a description of used dataset. Section 4 delivers information about the methodology of our research. Section 5 summarizes problems related to nowcasting of macroeconomic variables during the COVID-19 outbreak. Section 6 discusses the inconsistencies that are visible in the one year ahead forecasts. Finally, Section 7 concludes the paper.

2. Literature review

The COVID-19 shock has created unprecedented volatility in the macroeconomic time series, which strongly influences forecasting. During the period of the first Great Lockdown (March to May 2020), the average lifetime of macroeconomic forecasts was likely to not survive one month. Second, in the summer of 2020, forecasts prepared worldwide were systematically more pessimistic when compared to the future realizations; real-time economic surprise indices, such as presented in the work of (Scotti 2016), reached an all-time high.

In response, the academic literature on macroeconomic forecasting became focused on the correct estimation of traditional models, as well as developments of nowcasting techniques (Foroni, Marcellino, Stevanovic 2020; Lenza, Primiceri 2020). Researchers usually attempt to build complex solutions to either incorporate a real-time flow of information (Mamaysky 2020) or adapt epidemiological frameworks (Eichenbaum, Rebelo, Trabandt 2020). The application of such models has moderate predictive power – although various frameworks showed recovery after the first year of the pandemic, they did not foresee the rapid rebound and potential increase of inflation (McKibbin, Fernando 2021; Teng et al. 2022).

Although we do not want to depreciate these efforts, one needs to note that those outcomes are usually not publicly available. In addition to that, replication will exceed the capacity of business economists. Commercial work consumes a great majority of time; this involves the publishing of daily comments, as well as the providing of presentations or calls to both internal and external clients. This limits the possibilities for using complex econometrics. Therefore, their practical application may be dead-on-arrival.

The forecasts produced during economic crisis are usually imperfect; the errors are usually biased, and the revisions are sometimes irrational (Eicher et al. 2019). The irrationality of revisions implies that errors can be decomposed and explained by the publicly available information available at the time when the forecasts were prepared. The problems are often related to inaccurate representation of the effect of geopolitical events (Eicher, Kawai 2022) or changes in the fiscal policy (Cronin, McQuinn 2021) in the economic forecasts. The weak performance is present in the case of commercial economists and international institutions, such as the International Monetary Fund or European Commission – they often make similar mistakes (An, Jalles, Loungani 2018).

Nevertheless, a relatively low number of researchers are trying to answer this question: in which areas are forecasting professionals creating the biggest mistakes and how can we improve on said mistakes? This study aims to fill that gap. It presents a detailed analysis of the economic forecasts in Poland, where data availability of short-term macroeconomic projections is far greater than that of the most developed European nation.

This analysis is focused on the behaviour of financial business economists. The key thing to understand is that the goal of a commercial professional is not to minimize Root Means Squared Errors (RMSE) at any cost, but rather to represent their institution. This often results in herding behaviour (Frenkel, Mauch, Rülke 2020; Tsuchiya 2021) – a situation when the economists are aligning their forecasts towards the estimates of a few leading people who decided to amend the forecasts in the first place. There are several motivational biases including acquiring publicity – some of them have been presented in Rybacki (2020). This problem has been visible, especially during the COVID-19 pandemic. After the first lockdowns, analysts published numbers which had poor justification; this is because they were expected to present a view, e.g. for risk management purposes or public statements in the press.

This problem has been evident in Narodowy Bank Polski's macroeconomic survey of professional forecasters (Kowalczyk 2010); economists show very wide bands of uncertainty in 2020, as well as a declining risk in 2021. Such an assessment is mathematically controversial; the GDP growth for 2021 is strictly related to the previous year's performance. Therefore, such a result was unlikely to be produced by the formal macroeconomic model. This evidence highlights the judgmental role in the forecasting during the period of macroeconomic stress. Although such heuristics are both flawed and prone to biases, there is strong evidence that shows that human expertise is beneficial during periods of excessive uncertainty (Lawrence et al. 2006). The same approach was visible during the pandemic. The peer-reviewed papers from the NBP analysts, written at that time, were rather focused on the analysis of disaggregated data based on simple methodologies (e.g. Mućk, Rubaszek, Szafranek 2021) or informative case studies regarding viable options for monetary policy (Glapiński 2021). Simultaneously, Podkaminer (2021) started a discussion which highlighted potential flaws of reasoning based on the dynamic stochastic general equilibrium (DSGE), i.e. problems with ignoring heterogeneity and reliance on strong assumption about calibrated variables and formation of expectations. These problems were highly visible during the pandemic – DSGE models overestimated the role of uncertainty and duration of the economic slowdown (Brzoza-Brzezina, Kolasa, Makarski 2021).

We are focusing on the forecasts produced during the pandemic as they have much greater implications, as opposed to mere standard times; they shape the financial market expectations and, consequently, become a basis for policymaking. In particular, they are used to justify what scale of government interventions, such as financial shields, are required. The analysis of forecast accuracy does not allow for the general reasoning about normal times; statistical efficiency, in such cases, was presented in Rybacki (2021).

From the perspective of institutions, such as the statistical office or the central bank, such an evaluation should help to answer which areas' publicly available information give a more reliable basis to create forecasts.

3. Database

This analysis is based on the database of individual forecasts that participated in both the *Parkiet* forecasting competition for monthly nowcasts, during the years 2015 to 2020, and the *Rzeczpospolita* competition – during the year 2020.

The *Parkiet* monthly consensus poll contains information about every major indicator that is published by both Statistics Poland (GUS) and Narodowy Bank Polski on a continuous basis. These include the Purchasing Managers Index (PMI), Consumer and Producer Price Index (CPI and PPI), industrial production, retail sales, construction output, corporate employment and wages, unemployment rate, exports, imports, and current account (CA) balance. Macroeconomic forecasts usually describe the year-on-year growth. In the case of the PMI, the jury decided to use the index level, and in the case of foreign trade variables, EUR denominated figures. The CA balance is also presented as a level. In 2020, there were 24 participants; 22 of them (92%) represent banks or financial intermediaries. The other two participants represent think-tanks.

The consensus for the *Rzeczpospolita* forecasting competition is collected quarterly. In 2020, analysts provided information about the year-on-year growth of GDP, private consumption, gross fixed capital formation, CPI, and the unemployment rate level. There were approximately 30 participants. Again, a similar proportion of participants represent commercial financial institutions.

These two contests are recognized as the most prestigious competitions among the many financial institutions in Poland. The number of participants is higher, when compared to Narodowy Bank Polski's survey of professional forecasters (SPF). The panel is more balanced; throughout the year, there are practically no cases in which a participant failed to complete a survey. This is not the case with the SPF.

Furthermore, the poll is developed with constant contact with commercial economists. Therefore, it is scheduled to be perfectly synchronized with the estimation of nowcasts. This is not always true in the cases of the Bloomberg and Reuters consensus. For example, Bloomberg requires a short-term estimate of the flash CPI a week before data release. These estimates are made prior to the publication of the GUS statistical bulletin. Therefore, the results are frequently different from the polls that are later published by Reuters, the Polish Press Agency, and *Parkiet*.

4. Methodology

This section describes the methodology. The research is divided into two parts. In the first part, we analyse the simple descriptive statistics of forecasts errors for the short-term macroeconomic variables. We attempt to analyse the magnitude of forecast uncertainty of four macroeconomic indicators, which were the most affected by the pandemic (i.e. corporate employment, wages, industrial production, and retail sales).

The forecasts accuracy analysis usually describes outcomes of the following regressions (Ager, Kappler, Osterloh 2009; Dovern, Weisser 2011; Lewis, Pain 2015).

$$Outcome_t = a_0 + a_1 \cdot Projection_t + e_t \tag{1}$$

The weak form of forecast effectiveness states that parameter a_0 is equal to 0 and a_1 to one, i.e. the projection rationally describes outcome and the errors are totally random. The magnitude of the mean square root error should increase over time, similarly like the forecasts' uncertainty. However, the results of such regression are rather obvious during the times of crisis – forecasts are often biases. Therefore, we decided rather to analyse stylized facts related to COVID-19 crisis.

Our first analysis is based on the dispersion between the forecasts. We calculate an interquartile range (IQR) of individual estimates in the subsequent months of 2020. This statistic eliminates 25% of the most pessimistic and the most optimistic forecasts. We compare these values to the average levels from the years 2015 to 2019, separately, for each subsequent month. We also wish to verify whether analysts could lower their errors after the initial lockdowns in March to April 2020. We propose a simple equation:

$$\frac{IQR_t}{IQR_{avg,\,m}} = a_0 + a_1 \cdot t + e_t \tag{2}$$

where IQR_t is an interquartile range for the forecast at the time t, $IQR_{avg,\,m}$ is an average interquartile range for forecasts in the years 2015 to 2019 for the month m, a_0 and a_1 are estimated parameters, e_t is a random disturbance.

We expect a_1 to be:

1. Negative for activity forecasts, i.e. the industrial production and the retail sales.
2. Positive or statistically insignificant for the employment figures.

We expect to see lowering disagreement in the case of nowcasts for industrial production, retail sales, and corporate wages. Corporate employment nowcasts are likely to have elevated disagreement during all the researched periods.

Secondly, we attempt to analyse the efficiency of the forecasts and the consistency between revisions of long-term estimates based on panel models. This analysis is also based on the database of individual forecasts, which participate in the second competition (the *Rzeczpospolita* contest) for the best macroeconomic analysts. We analyse forecasts for the two macroeconomic indicators: GDP growth and the unemployment rate.

We attempt to answer whether forecasts were efficiently in line with the Nordhaus definition (Nordhaus 1987) in the strong form. This concept assumes that all publicly available information is utilized. Therefore, revisions should be totally unpredictable (i.e. information about previous forecasts should not give any clues on how they will be changed in the next months). Systemic errors were present in the Polish GDP forecasts – even before the pandemic (Rybacki 2021). The use of this approach in the time of crisis should provide greater insight in the behavioural aspects of forecasting. We propose a simple model:

$$d\,(forecast_t) = a_0 + a_1 \cdot d(forecast_{t-1}) + e_t \tag{3}$$

The notation is similar when compared to equation 1. We expect parameter a_0 to be different than zero. In such a case, published estimates have obvious one-sided biases. We also see whether parameter a_1 is negative and less than one. This implies that analysts are making excessive corrections, which are reverted in the next round of forecasts.

Second, we would like to verify whether the forecast revisions were consistent over time. The formal tests for rationality usually assume running the regression, where errors are explained by the vector of variables X_t, which were known by the forecaster at the time of producing the forecasts (Runkle 1989).

$$e_t = a_0 + a_1 \cdot X_t + e_t \tag{4}$$

In such a case our aim is to identify the variables, which statistically influence the error. Based on such variables, we can state that forecasters did not act rationally, as they do not include it in the model. The problem of this approach is to express the information set of the forecaster – we do not have data on the fiscal forecasts, which should be crucial in the case of the COVID-19 crisis.

Therefore, we proposed a simple regression which verifies the consistency of revisions between available variables. The increase in the unemployment rate should have a negative effect on the growth forecasts and consumption. We attempt to estimate a simple model where the revision of consumption forecast ($fConsumption_t$) is explained by the revision of the unemployment rate ($fLabor_t$). This formula is presented in equation 4.

$$d\,(fConsumption_t) = a_0 + a_1 \cdot d\,(fLabor_t) + e_t \tag{5}$$

We estimate the independent equations for each period and forecasts horizon. Our aim is to verify whether the relationship between these revisions is negative for each period. Then, we would like to check if the response is different in the case of negative and positive revision. Finally, in the case of the longer forecasts, we would like to discuss to what extent revisions are related to exogenous assumptions.

5. Nowcasting of monthly activity and labour market conditions after the COVID-19 outbreak

This section summarizes the accuracy of nowcasts that were published during 2020. Nowcasts are approximations of current economic conditions that are published prior to the official statistical office data release. The disagreement between the forecasters, consensus errors, and parameters of estimated models are all presented in Tables 1 to 4.

The biggest errors were recorded in April; the data published at that time describes the economic reality from March. Similarly, the scale of uncertainty in this month was also the highest during the whole of 2020. The interquartile ranges of forecasts are presented in Figure 1. Analysts were forced to forecast the effects of the lockdown – an unprecedented event. Given no evidence of such episodes in the past, these actions were blindly accepted.

Analysts improved their accuracy regarding the forecasting of retail sales; errors and disagreement decreased over time, most likely due to analysing real-time data from both debit and credit card payments.[1] This evidence is confirmed by the model; the a_1 parameter is statistically significant and is equal to -0.46. However, at the end of 2020, the disagreement between the forecasters was still twice as high as before the pandemic and amounted to two to three percentage points. Uncertainty was especially elevated during periods with a greater number of infections. For example, in September, the disagreement was over four times higher than in the years of 2015 to 2019.

Economic experts also had no major problems when it came to forecasting industrial production. During the years of 2015 to 2019, the interquartile range averaged slightly over one percentage point. We also observed similar values in the fourth quarter of 2020. The model confirms fading uncertainty; the estimated parameter a_1 for this variable is equal to minus 0.31.

From the third quarter onwards, wage forecasts didn't deviate from the usual trend either. At the end of the year, the disagreement between the forecasters was approximately 0.3 percentage point. Large fluctuations were only observed in the period of March to May. This resulted from the unclear impact of the anti-crisis government response. The effects of subsidizing compensations were difficult to assess by the commercial analysts. In the case of this variable, the estimated parameter a_1 is equal to -0.22.

Economists cannot effectively forecast employment in the enterprise sector. Normally, analysts make errors of 0.1 percentage point. They are also nearly unanimous in their forecasts. During the pandemic, these figures were multiple times higher; in June, the disagreement of forecasters was 16 times greater than what had been observed in previous years. At the end of the year, it was 5 times higher than in the years 2015 to 2019, despite even the large fluctuations of the headline figure having vanished.

This evidence is also present in the model. Although the estimated parameter a_1 is negative (-0.61), it is strongly influenced by the June reading. Therefore, the standard deviation of this parameter is high and contrary to the previous estimations, it is statistically insignificant. This evidence confirms the problem described in the previous paragraph.

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[1] An example of such an analysis, is the Santander report regarding consumption expenditure during the restrictions in November 2020, after the country was divided into the yellow and red COVID-19 zones.

6. Macroeconomic forecasting during the COVID-19 pandemic

This section summarizes the accuracy of long-term forecasts published during 2020, with a horizon of one to three quarters ahead. The model, which is based on equation 2, confirms a lack of efficiency in the case of GDP and in the unemployment rate forecasts. The results are presented in Tables 5 and 6.

A first glance at the consensus reveals that economists systematically presented an overly pessimistic picture of the unemployment rate. The evolution of the consensus duration is presented in Figure 2; the revisions are rather one-sided, so we can see a constant delaying of periods when unemployment was expected to increase.

Forecasts were systematically reduced across all horizons (i.e. from the incoming quarter to one year ahead). The biggest reductions were visible in the case of estimates with the lower horizon; within a quarter to publication, analysts lowered estimates – on average – by 0.6 percentage point. The magnitude for other horizons were slightly lower and amounted to 0.3–0.4 percentage point. The negative parameter a_1 suggests a tendency for excess revision; this is especially visible in the case of forecasts from Q2, in which analysts were predicting an imminent contraction of employment.

Analysts have also exaggerated the effects of the economic lockdowns in the case of the GDP forecasts, although the errors of these estimates are less one-sided. After restrictions were lifted in June 2020, economists started predicting a recovery. They were surprised in Q4 by the second wave of infections that resulted in another period of excessive negative errors. This evolution of consensus is presented in Figure 3.

The model parameters have similar interpretations like in the case of the unemployment rate. Systematic biases and excessive revisions were present in the economic debate in Poland – even prior to the COVID-19 pandemic (Rybacki 2021). The period of the pandemic is not different.

The analysis shows a lack of consistency between the revisions of consumption and the unemployment rate. Basic specifications (Table 7) show a positive correlation between amendments to the forecasts for these two variables. When analysts forecasted a better outlook for consumption, they could simultaneously be more pessimistic on the labour market conditions and vice versa. The relationship is statistically insignificant; still, it is worth considering why revisions of economic activity were detached from the labour market conditions.

We repeated the estimation separately for each period. The direction of revisions was intuitive in the first half of 2020; expectations of bigger unemployment resulted in a worse activity outlook. Nevertheless, the explanatory power of these equations is very weak; the r-squared coefficient is usually lower than 10%. During the second half of 2020, the relationship was broken and changes to the labour market assumption were insignificant. The average magnitude of revision – in consumption corresponding to changes in the labour market assumption – is much lower than in the case of the intercept, which captures exogenous factors like expectations of lockdown conditions. In the case of the longest horizon (three quarters ahead), the impact is three to six times lower. This is presented in Table 8.

7. Policy conclusions

The COVID-19 pandemic revealed a weak understanding of the labour market conditions among the Polish economists. Problems related to forecasting were visible in the case of identifying current conditions, as well as preparing long-term predictions.

If a single analyst is wrong, it is a problem of his or her negligence. However, when a community of analysts is overall incapable of presenting a reliable view on the labour market condition, it is a problem of both the fiscal and monetary authorities; their decisions may be based on a very inaccurate picture of the economy. There are three areas in which this should be investigated.

First, the data dissemination policies of the statistical office need to be reviewed. The likely reason behind the problem with both forecasting employment and unemployment is the lack of sufficient information about the process that is provided by the statistical office. The monthly disseminated statistics describe employment in the small, medium and big companies on the basis of employment contracts. The estimated number of jobs is equal to 6.5 million, which covers approximately only 40% of the total workforce (16.7 million). At the same time those companies hire people based on civil-law contracts, for example: contract of mandate (in Polish *umowa zlecenia*) or contract for specific work (in Polish *umowa o dzieło*). Statistics Poland (GUS) conducts surveys about such employment only once per two-years. According to the 2019 data there were approximately 1.4 million people employed based on such contracts. This employment is most volatile during downturns. Therefore, the survey DG-1, which is the basis for monthly statistics, should include a question about it. Broadening the mandate of GUS to gather more information may be an advantageous move.

It is likely that public statistics in Poland do not have all the necessary information about business--to-business contracts. Those are available real-time in the two registers: the Ministry of Development's CEIDG and GUS REGON. Unfortunately, this data is not disseminated in a user-friendly way – GUS publishes only a monthly snapshot without providing a time series. As a result, contrary to typical signalling information, this data is not widely commented by the economists and the press. Furthermore, the content of the register is problematic – according to the REGON data there are approximately 4 million sole proprietorships in Poland. The annual survey conducted by GUS suggests the number is closer to 2.5 million. The register contains information about uncooperating businesses, which requires verification.

Finally, greater attention should be directed towards the academic sector. The National Science Centre in Poland provides funding for various scientific research projects that analyse the shape of the labour market. Unfortunately, the pandemic highlighted that this accumulated knowledge is not supportive during economic downturns. The single academic project which attempted to improve knowledge about the labour market was *Diagnoza plus*, conducted by the GRAPE group based on a web survey with a relatively established methodology (Imai, Ratkovic 2014). Unfortunately, this approach failed in the pandemics – this was the single survey showing a fall in unemployment during the lockdowns. Of course, failures are inevitable – this is not a problem. However, the scarcity of the techniques is problematic. The current recruitment process does not consider the potential application of research in the grant mechanisms; furthermore, commercial experts do not assess the potential viability of the projects. A greater emphasis on these practical aspects should be beneficial.

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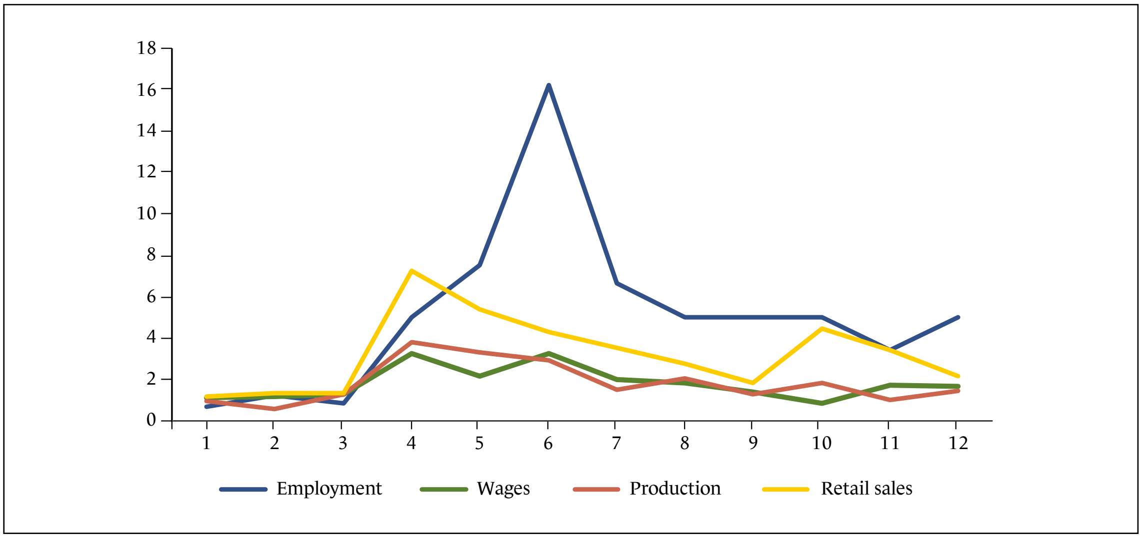
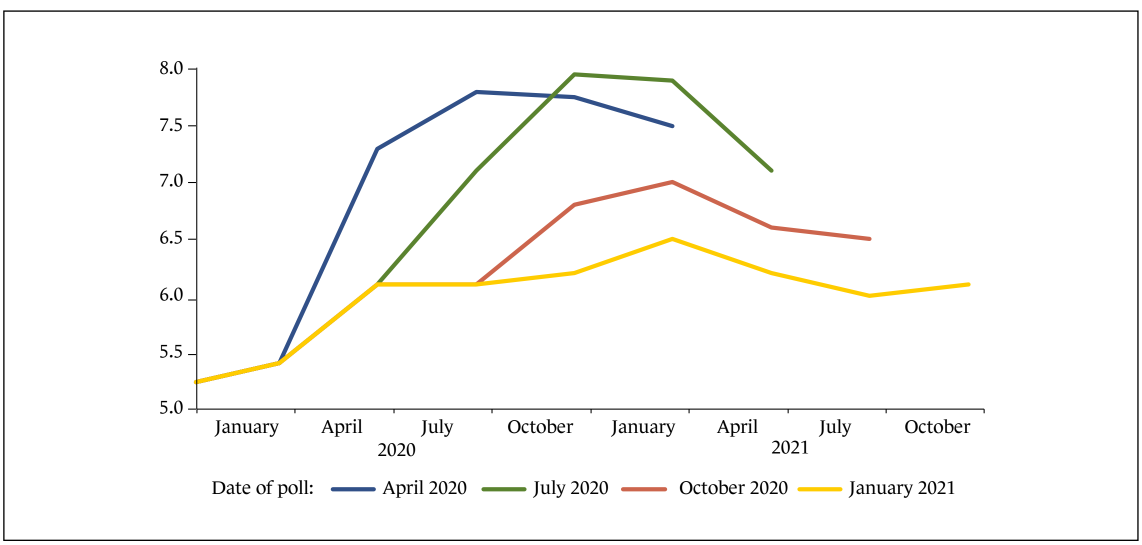
Appendix

Figure 1
Number of times the interquartile range of forecasts was higher than the average from 2015 to 2019 in the subsequent months of 2020



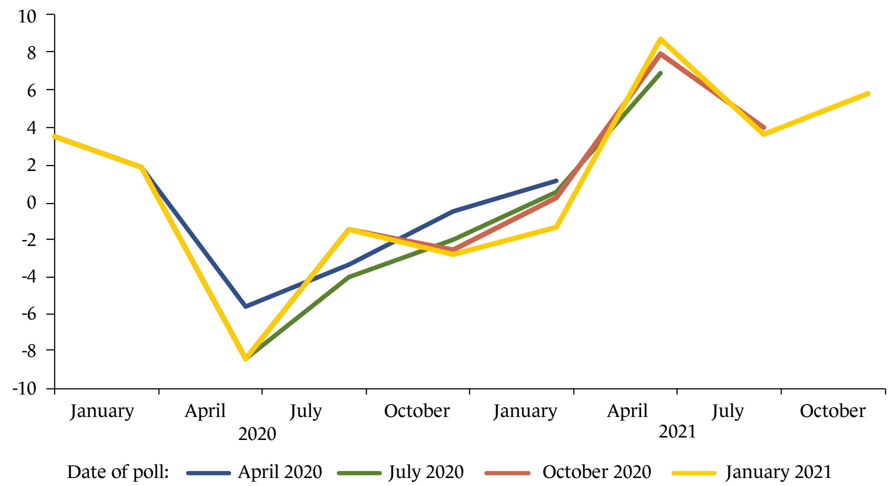
Source: *Rzeczpospolita* daily.

Figure 2
Unemployment rate consensus forecast under the COVID-19 pandemic



Source: *Rzeczpospolita* daily.

Figure 3
GDP growth consensus forecast under the COVID-19 pandemic



Source: *Rzeczpospolita* daily.

Table 1
Forecast characteristics – employment in the enterprise sector

Month of publication	Forecasts error		Forecasts disagreement	
	2020	median 2015–2019	2020	median 2015–2019
1	0.0	0.1	0.1	0.1
2	1.1	0.8	0.8	0.7
3	0.0	0.1	0.1	0.1
4	0.5	0.1	0.3	0.1
5	1.5	0.0	0.5	0.1
6	0.6	0.1	0.6	0.0
7	0.5	0.1	0.4	0.1
8	0.8	0.1	0.3	0.1
9	0.2	0.1	0.4	0.1
10	0.1	0.0	0.3	0.1
11	0.1	0.1	0.3	0.1
12	0.2	0.1	0.3	0.1
	Estimated parameters			
	parameter	standard deviation	T-statistics	P-value
a_0	11.39	3.99	2.85	0.02
a_1	-0.61	0.47	-1.28	0.24

Note: this model is based on the equation presented in formula 1.

Table 2

Forecast characteristics – corporate wages in the enterprise sector

Month of publication	Consensus – forecasts error		Forecasters' disagreement	
	2020	median 2015–2019	2020	median 2015–2019
1	0.1	0.7	0.8	0.7
2	0.3	0.4	0.9	0.8
3	0.8	0.1	0.6	0.5
4	0.1	0.9	1.7	0.5
5	2.5	0.6	1.5	0.7
6	0.3	0.5	1.7	0.5
7	2.5	1.0	1.2	0.6
8	1.1	0.3	1.1	0.6
9	0.1	0.2	0.7	0.5
10	1.2	0.5	0.4	0.5
11	0.0	0.6	0.7	0.4
12	0.4	0.6	0.8	0.5
	Estimated parameters			
	parameter	standard deviation	T-statistics	P-value
a_0	3.78	0.60	6.27	0.00
a_1	-0.22	0.07	-3.10	0.02

Note: this model is based on the equation presented in formula 1.

Table 3
Forecast characteristics – industrial production

Month of publication	Consensus – forecasts error		Forecasters' disagreement	
	2020	median 2015–2019	2020	median 2015–2019
1	2.2	1.4	2.2	2.3
2	0.8	1.3	1.5	2.8
3	2.9	1.2	1.8	1.4
4	0.2	2.2	6.4	1.7
5	12.2	2.4	6.8	2.1
6	0.6	1.1	5.3	1.8
7	7.8	0.6	2.9	2.0
8	3.2	0.7	4.7	2.3
9	1.3	2.4	2.2	1.7
10	2.5	0.9	2.0	1.1
11	0.0	1.2	1.5	1.5
12	2.1	0.6	2.8	2.0
	Estimated parameters			
	parameter	**standard deviation**	**T-statistics**	**P-value**
a_0	4.63	0.57	8.17	0.00
a_1	-0.31	0.07	-4.65	0.00

Note: this model is based on the equation presented in formula 1.

Table 4
Forecast characteristics – retail sales

Month of publication	Consensus – forecasts error		Forecasters' disagreement	
	2020	median 2015–2019	2020	median 2015–2019
1	0.1	2.1	1.9	1.7
2	1.0	1.8	1.7	1.3
3	3.2	0.5	1.5	1.1
4	7.0	1.5	9.0	1.2
5	3.9	1.8	7.7	1.4
6	4.3	0.6	4.9	1.1
7	1.7	0.5	3.2	0.9
8	3.6	0.5	3.0	1.1
9	2.1	0.7	2.1	1.1
10	0.1	1.7	2.9	0.7
11	1.7	0.7	3.4	1.0
12	2.1	1.6	2.5	1.2
	Estimated parameters			
	parameter	**standard deviation**	**T-statistics**	**P-value**
a_0	7.61	1.31	5.80	0.00
a_1	-0.46	0.16	-2.98	0.02

Note: this model is based on the equation presented in formula 1.

Table 5

Revisions of unemployment rate forecasts – panel model

Horizon (quarters)	1	2	3
a_1	-0.40 (0.06, 0.00)	-0.30 (0.06, 0.00)	-0.36 (0.06, 0.00)
a_0	-0.59 (0.08, 0.00)	-0.36 (0.09, 0.00)	-0.31 (0.09, 0.00)
Periods	3	3	3
Cross sections	31	31	31
Observations	93	93	93
R-squared	0.69	0.60	0.66

Notes:
This model is based on the equation presented in formula 2. Negative parameter a_0 denotes excessive pessimism regarding labour market conditions amongst the forecasters; their estimates of the unemployment rate were systematically lowered with the next surveys.

Table 6

Revisions of GDP forecasts – panel model

Horizon (quarters)	1	2	3
a_1	-0.25 (0.06, 0.00)	-0.27 (0.09, 0.00)	-0.44 (0.09, 0.00)
a_0	-1.78 (0.26, 0.00)	-1.05 (0.27, 0.00)	-1.12 (0.22, 0.00)
Periods	3	3	3
Cross sections	31	31	31
Observations	93	93	93
R-squared	0.58	0.55	0.50

Notes:
This model is based on the equation presented in formula 2. Negative parameter a_0 denotes excessive pessimism regarding economic activity amongst the forecasters; their estimates of GDP growth were expected to improve with the next surveys.

Table 7

Revisions of consumption forecasts – panel model

Horizon (quarters)	1	2	3
Revision – unemployment	0.33 (0.26, 0.21)	0.25 (0.19, 0.19)	0.11 (0.21, 0.61)
Constant	-0.80 (0.31, 0.01)	-0.53 (0.27, 0.06)	0.13 (0.32, 0.68)
Periods	3	3	3
Cross sections	31	31	31
Observations	93	93	93
R-squared	0.38	0.35	0.38

Notes:
This model is based on the equation presented in formula 3. The positive parameter a_1 shows that the assumption over the labour market played a relatively minor role in shaping forecasts for economic activity even for the longer horizons, when employment assumptions should be more significant.

Table 8

Revisions of consumption forecasts (3Q ahead) – cross section estimates

Poll	April 2020	July 2022	October 2020	January 2021
	Model parameters			
Revision – unemployment	-0.66 (0.31, 0.04)	-0.49 (0.34, 0.16)	0.70 (0.65, 0.29)	-1.22 (0.68, 0.08)
Constant	-1.64 (1.08, 0.14)	-0.14 (0.62, 0.82)	2.03 (0.57, 0.00)	-1.82 (0.45, 0.00)
R-squared	0.13	0.07	0.04	0.10
Actual data – average revision of the:				
Unemployment rate	3.0	-0.7	-0.5	-0.4
Consumption growth rate	-3.6	0.2	1.7	-1.3
What magnitude of revision in consumption forecast is explained by the:				
Change in the labour market assumption	-2.0	0.3	-0.3	0.5
Exogenous factors (constant)	-1.6	-0.1	2.0	-1.8
Implied random disturbance	0.0	0.1	0.0	0.0

Note: this model is based on the equation presented in formula 3 – within a single period.

Prognozowanie makroekonomiczne: lekcje z szoków zewnętrznych

Streszczenie

Celem tego badania jest przedstawienie problemów związanych z prognozowaniem gospodarczym, które pojawiają się przy silnych szokach zewnętrznych, np. w okresie pandemii COVID-19 w 2020 r. Pandemia wywołała niespotykane dotychczas wahania zmiennych makroekonomicznych. Do ich śledzenia konieczne stało się m.in. analizowanie danych o bardzo wysokiej częstotliwości. Przykładowo progności związani z sektorem bankowym zaczęli publikować informacje dotyczące zagregowanych wydatków swoich klientów pochodzące z kart kredytowych.

W pierwszej części badania analizujemy, jak ewoluowała niepewność dotycząca wskaźników miesięcznych na podstawie panelu prognoz miesięcznika *Parkiet*. Za pomocą prostego modelu szeregów czasowych pokazujemy, że po wstępnym szoku związanym z zamrożeniem aktywności gospodarczej w marcu i kwietniu ekonomistom udało się znaleźć metody, które pozwoliły ograniczyć niepewność prognoz dotyczących aktywności gospodarczej, np. produkcji przemysłowej czy sprzedaży detalicznej. Niemniej jednak zawodowi progności mieli duże problemy z prognozowaniem sytuacji na rynku pracy, prawdopodobnie z uwagi na mniejszą dostępność informacji oraz kształt statystyk publicznych prowadzonych przez Główny Urząd Statystyczny.

W drugiej części odpowiadamy, czy prognozy długoterminowe charakteryzowały się efektywnością oraz czy ich rewizje były spójne i racjonalne. Przeprowadziliśmy testy statystyczne zaproponowane przez noblistę Williama Nordhausa oraz oszacowaliśmy model ilościowy analizujący interakcję między rewizjami. Badanie pokazuje, że występowały liczne przypadki nieefektywności, ponownie głównie w analizie sytuacji na rynku pracy. Szacunki spadku PKB były odklejone od ocen zmian zatrudnienia. Ekonomiści potrafili prognozować podobną skalę załamania przy założeniu dużego oraz niewielkiego wzrostu bezrobocia. Część rewizji była trudna do uzasadnienia na gruncie teoretycznym – np. analitycy pomniejszali prognozy wydatków konsumpcyjnych, jednocześnie pokazując lepsze długoterminowe perspektywy rynku pracy.

Praca kończy się podsumowaniem wskazującym problemy dotyczące statystyki rynku pracy, które mogły powodować wymienione zjawiska. Główny Urząd Statystyczny bardzo rzadko analizuje sytuację osób pracujących na umowach zlecenia czy o dzieło, a tego typu zatrudnienie ulega największym zmianom podczas kryzysów. Częstsze badanie tych segmentów rynku pracy prawdopodobnie poprawiłoby jakość prognoz.

W dyskusji zwracamy również uwagę na małe zaangażowanie środowiska akademickiego w prognozowanie podczas pandemii. Na początku pandemii COVID-19 powstał tylko jeden projekt, który próbował śledzić sytuację na rynku pracy (Diagnoza plus). To zdecydowanie mało. W naszej ocenie konieczna jest szeroka dyskusja nad systemem zachęt dla akademików, np. w postaci grantów Narodowego Centrum Nauki, który prowadziłby do większego zaangażowania w krytycznych momentach cyklu biznesowego dla polskiej gospodarki.

Pomimo upływu ponad roku od opisywanych wydarzeń przedstawione problemy są nadal aktualne. Wojna w Ukrainie oraz potencjalny kryzys energetyczny w państwach Unii Europejskiej mogą spowodować wystąpienie problemów z prognozowaniem, analogicznych jak w czasach pandemii COVID-19.

Słowa kluczowe: prognozowanie PKB, prognozowanie rynku pracy, COVID-19, trafność prognoz, spójność prognoz