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Improving forecasting abilities of business students: The effectiveness of nudges and performance heterogeneity

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A R T I C L E I N F O

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A B S T R A C T

The study examines how a simple nudge intervention in class materials improves the forecasting performance of business students. In an experiment with a sample of economics and management graduate students, we examined forecasting performance by calculating the Brier score for their predictions on twenty forecasting items. A nudge prompted students to attend to evidence-based sources and consider multiple possible future scenarios. We found no significant difference between the treatment and control groups. Exploratory analysis suggested that the nudge increased forecasting performance among the students with the overall poorest class performance. The results show that for underperforming students, information provision nudges can improve their educational outcomes and business-related skills.

1. Introduction

Nudge theory posits that small changes in the choice architecture, i.e., the way options are presented or the environment in which decisions are made, can significantly improve behavior without restricting freedom of choice. Nudges utilize changes in the environment to steer behavior without changing incentives or restricting any options (Thaler & Sunstein, 2009).

Nudge theory is theoretically rooted in dual-process cognitive theory: some nudges target automatic, Type 1 processes (quick, habitual behaviors; often referred to as System 1), whereas others prompt more reflective, Type 2 thinking (often referred to as System 2) (Hertwig & Grüne-Yanoff, 2017; Kahneman & Klein, 2009). Therefore, nudges work via changes in choice architecture that opt to circumvent the cognitive shortcomings or inertia of our minds in simple, cheap, and freedom-preserving ways that steer our decisions in positive ways (Sunstein, 2014; Thaler & Sunstein, 2009). These interventions have produced varying effects, with different meta-analytical evidence ranging from null (Hu et al., 2025; Maier et al., 2022) to moderate effects (Mertens et al., 2022). However, the discussion of the heterogeneity of nudge effects is still underdeveloped, even though it might prove essential to shed light on the varying effects of nudge interventions (Bryan et al., 2021), as recent work suggests that delivering a nudge selectively might increase intervention effects (Murakami et al., 2022). Moreover, interindividual and contextual effects are understudied in nudging (Houdek, 2024; Marchiori et al., 2017; Rouyard et al., 2022), while factors such as initial performance in the targeted behavior have been shown to influence the efficacy of nudges (Franklin et al., 2019).

Nudges represent important and easily applicable tools in educational settings, and they have proved useful in earlier phases of the educational process (Damgaard & Nielsen, 2018; Weijers et al., 2021). Educational nudges are classified based on their intended influence – whether they primarily target automatic behaviors (Type 1) or encourage reflective thinking (Type 2) – as well as their level

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of transparency. By distinguishing between these types, researchers and educators can design interventions better suited to specific contexts, ensuring that nudges align with the cognitive processes they aim to influence (Weijers et al., 2021). Several behavioral interventions have been examined in the context of education; for instance, mindset interventions (i.e., Type 2) have been recently shown to work in improving students' math grades; however, this effect was conditional on the attitudes of the teacher towards mindset intervention (Yeager et al., 2019, 2022). These findings were recently elaborated on, where a similar pattern emerged even with controlling for confounders, and the results were consistent across a representative sample of adolescents (Hecht et al., 2023).

Nudges are also used in the adoption of school-to-parent communication technologies (Bergman, 2020), improving completion rates in online education (Kizilcec et al., 2020), or they have been suggested for altering choice architecture (i.e., Type 1) when parents select a school for their children (Rauch, 2015). Furthermore, behavioral interventions and nudges have been used to help disadvantaged students utilize governmental support programs for college and increase the likelihood of college attendance (Bettinger et al., 2012); however, this effect does not seem to scale up and has an effect on a more local level (Bird et al., 2021). Besides using financial support, nudging has been explored in taking out student loans, and increased loans were linked with improved GPA, gained credits, and transfers to public colleges (Marx & Turner, 2019).

The change from secondary education to university holds challenges for many students (Meer & Chapman, 2014). Though theoretical guidelines for the use of nudges in graduate education were proposed (Bailes & Hoy, 2014), more empirical examination needs to be undertaken. To this end, we chose a nudge application for the forecasting domain, where graduate students exhibit significant biases and fallacies (Lawrence et al., 2006). Although forecasting skills are essential, they are underemphasized in business curricula, even though research indicates they can be effectively taught (Giullian et al., 2011).

Forecasting skills are improvable by traditional training approaches or by using mathematical models (Mellers et al., 2015; Nesvold & Bratvold, 2022). The most common forecasting models in higher education consist of regression, simulation, and data mining (Sinuany-Stern, 2021). These core forecasting techniques have remained broadly used, and educational approaches have evolved to incorporate advanced software tools and gamification strategies to improve learning outcomes (Hanke & Weigand, 1994; Legaki et al., 2019).

However, recent work suggests that nudges might be comparable in effects to statistical model training (Mertens et al., 2022). Research has shown that cognitive biases significantly influence how people estimate uncertain or risky outcomes and formulate predictions. Particularly, anchoring biases, under- and over-confidence influence the distribution of forecasting errors (Theodossiou & Ellina, 2020; Tversky & Kahneman, 1974) as well as availability bias (Harvey, 2007) and confirmation bias (Mokanov, 2023; Nickerson, 1998). Nudge theory opts to alter the decision-making environment in a way to counteract or leverage these biases by subtly changing how choices or information are presented (Sunstein, 2014). For example, providing a comparative benchmark or base-rate information can reduce overconfidence and improve forecasting by presenting broader data sources (Boz-Yılmaz & Boduroglu, 2024). Cognitive shortcomings described in dual-process theory lead to various behavioral and cognitive biases. In turn, nudges can be an effective tool to either harness biases or neutralize them: a well-known Type 1 nudge is the use of default options to utilize inertia (Jachimowicz et al., 2019), whereas a Type 2 nudge might present a salient reminder or information to encourage deliberate consideration (Baker et al., 2016; Kizilcec et al., 2020; Milkman et al., 2021).

1.1. Why forecasting is bias-prone and how nudges can help

A common problem identified in decision-making and evaluation of the future states is a tendency to focus on single-point estimates, which are more susceptible to biases and neglect of uncertainty (Buehler et al., 1997; Tversky & Kahneman, 1974). Accounting for a multitude of previous experiences, contextual cues, or relevant knowledge–known as distributional data–makes one less inclined to rely only on single-point estimates (Kahneman & Tversky, 1977) as well as other cognitive biases associated with erroneous forecasting; thus, we hypothesize that targeting neglect of distributional data might improve forecasting ability (see Table 1). Therefore, according to our hypothesis, we tested a simple Type 2 transparent nudge that influenced the prediction-eliciting environment by emphasizing distributional data in a forecasting tournament in a management graduate course.

The intervention was designed to target an upstream forecasting error tendency, i.e., narrow focusing (single-scenario thinking),

Table 1
Neglect of distributional data as an upstream source of several forecasting biases, and the intended role of the nudge.

Biases confounding forecasting	Improving forecasting by using distributional data nudge
Anchoring bias: a tendency to over-rely on initial information encountered when making a decision (Tversky & Kahneman, 1974).	Distributional data encourages considering multiple reference points; thus, reducing the influence of an initial anchor.
Overconfidence: excessive confidence leading to underestimating uncertainty (Moore & Healy, 2008).	Distributional data makes the uncertainty explicit. Emphasizing multiple future states and sources of information helps calibrate forecasts.
Availability bias: overweighting the likelihood of events based on information that is easily available and retrievable from memory (Tversky & Kahneman, 1973).	Distributional data helps expand information search strategies and reduce over-reliance on immediately accessible cues.
Confirmation bias: unjust favoring of information supporting preexisting beliefs while discounting contradicting information (Nickerson, 1998).	Distributional data helps present multiple scenarios and sources of information that might go against preexisting beliefs; thus helping to achieve a more balanced overview of relevant information.
Neglect of base-rate information: this bias involves disregarding the underlying statistical frequencies or prior probabilities when making judgments (Bar-Hillel, 1980).	The distributional data point to the use of base-rate information whilst making a prediction; thus reducing the propensity to use single-point estimates.

which we operationalize as neglect of distributional data, rather than to debias one specific bias in isolation. Conceptually, narrow focusing is expected to manifest in several downstream biases that commonly impair probabilistic judgment (e.g., anchoring on a salient value or initial intuition, overconfidence due to insufficient consideration of uncertainty, availability-driven sampling of evidence, and selective search that is consistent with pre-existing beliefs). Accordingly, our nudge did not introduce any anchor value, benchmark probability, or new informational content; instead, it prompted participants to (i) consider multiple plausible future states and (ii) consult credible evidence sources, thereby encouraging a broader reference class and more distribution-sensitive reasoning.

2. Methods

2.1. Sample

We collected data for $N = 153$ students who participated in the study out of $N = 184$ invited students enrolled in the class; $n = 31$ students either dropped out of the class or missed the deadline. Additionally, seven students were excluded from the dataset because they did not pass the class. We randomly assigned participants to two conditions: a nudge condition ($n = 69$) and a control condition ($n = 84$). Fifty-six percent of our sample were women.

2.2. Procedure

We conducted a preregistered experiment in which we randomly assigned graduate students to two conditions: a nudge condition and a control condition. Students took part in the forecasting tournament – an incentive-compatible task – in exchange for class credits contributing to the final grade. Furthermore, credit was conditional on students' performance compared to their classmates. The managerial decision-making class is a mandatory part of the curriculum for a Master's degree in Management, which is graded based on a written examination, a group case study, and a forecasting tournament. Data for forecasting performance were collected online in two measurements with a month-long delay.

2.3. Materials

This section describes the forecasting task, the resolution of forecasted events, the computation of forecasting performance, and the intervention. Each item in the forecasting tournament was a future event for which participants provided a probability estimate between 0 and 100% indicating how likely they believed the event would occur. The actual realized outcome of each item was then binary (the event either occurred = true, or did not occur = false).

The forecasted events were selected such that their outcomes were not known at the time of elicitation and could only be determined after a fixed time horizon. Predictions were therefore revealed as true or false approximately three months after the first measurement, when each event had either occurred or not occurred. Outcomes were based on verifiable real-world developments that the authors tracked and subsequently coded.

Data collection was conducted in two waves separated by approximately one month. This design served two purposes. First, to ensure that all items remained valid future events at the time of elicitation. Second, to reduce respondent burden, fatigue, and random guessing by limiting each wave to 10 forecasting items. Forecasting items included predictions such as (the rest of the items can be found in Appendix A):

"*One Euro (1 EUR) will be equivalent to or higher than 24.*5 CZK *as of December 2nd, 2022.*"

The nudge condition used identical prediction-eliciting items and added a sentence prompting students to pay attention and consider multiple factors before they made the prediction: "*Please, consider all possible future states and credible sources of information, and make your prediction.*" Each item was nudged with the above-described prompt. Moreover, each forecasting item, regardless of condition, was supported by a URL which was later used to check whether the forecasted event occurred or not.

We did not elicit participants' pre-existing beliefs about the specific domains before they made predictions; instead, we relied on random assignment to balance such beliefs across conditions. The nudge was developed by the authors; we prioritized a minimal, theory-driven formulation that could be implemented at minimal cost within a course exercise. Thus, instead of focusing on specific ways, we aimed at altering choice architecture with a simple prompt that might potentially help in various forecasted topics. Moreover, we deliberated on the tradeoff between complexity and simplicity of the nudge, and kept our intervention intentionally minimal, freedom-preserving, and embedded in the choice architecture consistent with nudge theory (Sunstein, 2014). Moreover, even simple text-based interventions and nudges have been shown to improve decision-making (Hallsworth et al., 2017; Kraft & Rogers, 2015; Milkman et al., 2021; Van de Calseyde & Efendić, 2022).

Lastly, after predictions were made and outcomes realized, we calculated a Brier score as a dependent variable reflecting one's forecasting performance. The Brier score was calculated as the mean squared difference between forecasted probability and actual outcome across all forecasting items (Ferro, 2007). A lower Brier score indicates more accurate forecasting, as it represents a smaller gap between predicted probabilities and observed results. In contrast, a higher Brier score reflects greater forecasting errors, signalling less alignment between predictions and actual outcomes. The Brier score is a proper scoring rule for probabilistic forecasts of binary outcomes, meaning that it incentivizes honest probability reporting and penalizes guessing (Gneiting & Raftery, 2007). Furthermore, it is commonly used in forecasting tournaments and large-scale studies on forecasting (Atanasov et al., 2017; Mellers et al., 2014).

Additionally, we included in the analysis a final grade from the class indicating overall performance, which consisted of a subset of activities, including a standardized written exam and a group case study evaluated by a committee of course instructors.

3. Results

To compare the effectiveness of the nudge on forecasting performance, we conducted a Welch Two-Sample *t*-test. The mean Brier score for the nudge condition was $M = .24$ ($SD = .05$) while the mean for the control condition was $M = .25$ ($SD = .06$). The preregistered expected difference between the Brier scores of the two groups was not significant, $t(142.91) = .70$, $p = .48$. We also report several exploratory analyses which were not a part of our preregistered analysis plan.

We divided the sample according to the median course performance after excluding forecasting points, creating low-performance ($n = 71$) and high-performance ($n = 75$) groups. The nudge had a significant effect on underperformers, leading to a decrease in the Brier score, $t(67.99) = 2.61$, $p = .01$, with the mean for the control group being $M = .31$ ($SD = .04$), and the mean for the nudge group being $M = .29$ ($SD = .03$) (see Fig. 1). On the other hand, nudging best-performing students while making a prediction had no effect on the performance, $t(73.11) = -.82$, $p = .42$. The mean for the control group was $M = .20$ ($SD = .04$), and the mean for the nudge group was $M = .21$ ($SD = .03$).

We also conducted an additional exploratory analysis to test whether the nudge affected forecast conservatism (i.e., whether forecasts became less extreme and more concentrated around 50%). For each participant, we computed a forecast extremity (sharpness) index defined as the mean absolute deviation from .50 across all items, i.e., extremity = mean($|p - 0.50|$), where p is the participant's probability forecast rescaled to the [0,1] interval. Lower values indicate more conservative forecasts. The mean extremity was the same for both groups; $M = .28$, $SD = .05$ in the nudge condition and $M = .28$, $SD = .05$ in the control condition. This difference was not statistically significant, $t(142.37) = -.12$, $p = .90$. Thus, the nudge did not appear to operate merely by making forecasts more conservative.

We correctly anticipated that forecasting performance would correlate with overall class performance ($r = -.21$, $p = .009$) even though the forecasting exercise consisted only of 5% of the grade. We also explored differences in gender regarding forecasting abilities. We found no difference in gender and forecasting ability, $t(142.48) = -1.18$, $p = .24$, or gender and class performance, $t(143.24) = -1.44$, $p = .15$.

4. Discussion

We explored how an informational nudge to consider distributional data could improve the forecasting performance of management students. We did not find support for a preregistered overall effect; however, an exploratory analysis showed that the nudge helped the below-average students. Differences in nudge effectiveness across performance levels underscore the importance of accounting for heterogeneity (Bryan et al., 2021) and suggest that behavioral interventions may be particularly beneficial for individuals with lower initial performance (Franklin et al., 2019). Importantly, observed improvement in forecasting performance among lower-performing students does not appear to be driven by a shift toward more conservative probability estimates. Our exploratory analysis showed no difference between the nudge and control conditions in forecast extremity, indicating that the nudge did not simply steer participants to move their predictions closer to 50%. Therefore, our finding suggests that improved performance was not achieved by being more conservative but rather reflects improvements in probabilistic accuracy. Furthermore, we did not observe differences in nudge effects across genders, even though the previous literature shows that nudges might produce different effects across genders; however, more robust nudges such as defaults or combining nudge interventions with a financial incentive varied in effect

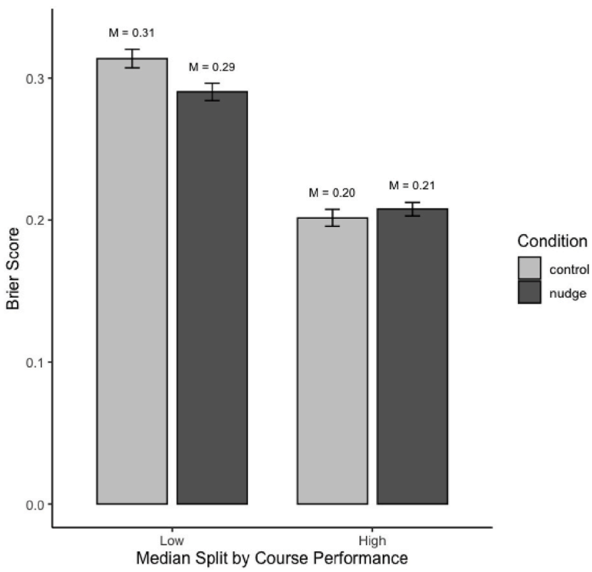

Fig. 1. Brier score split by median overall course performance.

across genders (Czap et al., 2018; He et al., 2021).

The present study suggests that a simple nudge can help reduce performance disparities among students by supporting those with weaker initial performance. This is particularly relevant given that nudges are currently understudied in the context of education, with only about 4% of nudges being dedicated to education in a review from 2018 (Szaszi et al., 2018). More recent work explores how teachers implicitly use nudges in their teaching (Weijers et al., 2024). Nudges have been explored in helping disadvantaged students apply for universities (Ilie et al., 2022; Kozman & Sanders, 2019). However, less empirical work has been done on graduate-level nudging; for instance, using nudges for student engagement might be a fruitful avenue into research; however, types of nudges and contextual effects need to be further studied (Graham et al., 2017). Thus, the present research contributes to exploring nudges in business graduate-level education and showcases that educational experiments might help underperforming students, consistent with previous use of educational games, e.g., in a forecast sharing game in supply chain management (Chen et al., 2023).

Due to the exploratory nature of the analysis, the observed effects should be interpreted with caution and require confirmation in future studies. The need for such follow-up work is consistent with a broader challenge in the nudging literature, namely the limited understanding of for whom interventions work, in which contexts, and through which mechanisms (Ingendahl et al., 2021; Marchiori et al., 2017). The present findings help to inform future research by highlighting the importance of performance-based heterogeneity. In line with this perspective, our results emphasize the value of theory-driven nudges that explicitly account for situational factors and underlying mechanisms (Houdek, 2024).

There are some limitations of our study and thus opportunities for follow-up research. Notably, information nudges might not have the strongest effects when compared with defaults or other types of nudges (Graham et al., 2017; Tor, 2020). We aimed to have an underlying mechanistic hypothesis explaining why forecasting should be improved by pointing to the distributional data. Even though nudges are advantageous in their simplicity and ease of use, forecasting is a complex phenomenon, and future studies might select a specific bias that would be targeted in a more specific manner than our strategy of searching for an upstream cause. Furthermore, we could not control for attrition among the students. Attrition may have introduced bias if students who were more likely to underperform–and who appear to benefit most from the nudge–were also more likely to drop out of the course or miss the forecasting task. In this case, the observed improvement among underperforming students would likely represent a conservative estimate of the nudge's effect.

Moreover, underperformers might have been more motivated by the incentive of class credit; such incentives were proven relevant in tournament-style settings (Vandegrift et al., 2007) and widely used to improve grades (Houdek et al., 2026). However, in regards to the results from the present study, we would expect increased motivation by underperformers to be present in both experimental conditions. Thus, the fact that lower-performing students in the nudge condition outperformed their counterparts in the control condition suggests that the observed effect cannot be attributed solely to incentive-driven motivation and may therefore underestimate the true effect of the nudge for underperformers.

Furthermore, because the nudge was embedded in each prediction-eliciting question, we did not include an attention check or a manipulation check, even though we believe that the nudge's visibility and the incentive-compatible nature of the task ensured adequate data quality. Implementing a manipulation check would have required participants to explicitly articulate or reflect on how they processed the prompt (e.g., by writing out their reasoning or engaging in an introspective exercise), which would have altered the nature of the intervention and shifted it away from a minimal informational nudge toward a more effortful, instructional task (Banerjee & John, 2024). Nevertheless, future research could deliberately incorporate such reflective manipulation checks, as requiring students to externalize their reasoning may itself function as a pedagogical tool and potentially amplify intervention effects. In this manner, cognitive effects of such prompts (e.g., metacognitive checking of whether one's knowledge is sufficient, broader evidence search, and confidence calibration) could be differentiated from their downstream behavioral effects on forecast accuracy.

Next, future research ought to examine whether educational nudges influence the trade-off between false alarms and missed events in ways analogous to forecast warning and risk-communication paradigms. This literature distinguishes the behavioral consequences of false alarms versus misses and shows that communicating uncertainty probabilistically can improve decision quality and adaptive responses under risk (Hembach-Stunden et al., 2024; LeClerc & Joslyn, 2015; Miran et al., 2018).

Lastly, in educational settings, we might consider alternative behavioral interventions instead of nudges. Namely, boosts could be used not to circumvent cognitive shortcomings but rather to capitalize on heuristics and build competencies in decision-making related to forecasting and intertemporal choices (Grüne-Yanoff & Hertwig, 2016; Hertwig, 2017). Whereas nudges subtly alter the environment to influence behavior and therefore are not easily scalable, as they are tailored specifically to a given decision-making context; boosts aim to enhance decision-makers' general competencies and knowledge. Usually, boosts aim to foster competencies through education based on heuristics; for instance, a boost intervention might train students in forecasting techniques in a way that would decrease bias in their predictions across topics. Therefore, boosts might be particularly useful in an educational setting because they do not rely on context-specific changes to the choice architecture. Moreover, boosts emphasize competence building, which is closely aligned with the aims of education to strengthen people's capacity to make informed choices by imparting actionable, procedural knowledge and supporting learners' agency (Herzog & Hertwig, 2025). Even though both approaches share a goal of improving decisions and behaviors, they differ in their theoretical underpinnings. Nudges seek to provide changes within the environment, and boosts, on the other hand, aim at developing new skills (Grüne-Yanoff et al., 2018). In turn, nudging and boosting might be complementary in addressing heterogeneous contexts and interindividual differences (Houdek, 2024; Franklin et al., 2019). Perhaps, higher performing students in the present study might benefit more from a boosting approach as opposed to nudging. Importantly, interventions need not be long to produce robust and long-term effects, as was demonstrated in the case of forecasting (Mellers et al., 2014); thus, education ought to leverage behavioral insights for improving educational outcomes in a time-sensitive and cost-effective manner.

5. Conclusion

The nudge intervention, prompting management graduate students to consider possible future scenarios and evidence-based sources of information before answering prediction-elicitation questions, did not affect their forecasting performance. However, an exploratory analysis showed that nudging improved forecasting performance in suboptimal performers. These findings contribute to nudging research in graduate education and encourage future exploration of tailored behavioral interventions to enhance educational outcomes.

CRediT authorship contribution statement

Nicolas Say: Writing – review & editing, Writing – original draft, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Lucie Vrbová:** Writing – review & editing, Methodology. **Petr Houdek:** Writing – review & editing, Supervision, Methodology, Conceptualization.

Ethics

Ethical approval was waived by the local Research Ethics Committee at the Center of Science and Research at the Faculty of Business Administration at the Prague University of Economics and Business in view of the low-risk nature of the study's design.

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Declarations of interest

None.

Appendix A

A full list of items that were used in the forecasting experiment. Items were translated from Czech, and each item had an original source in the form of a URL link, which would be used to confirm the final outcome of the prediction:

1. The price of 1 kg of caraway bread will be more than 39.30 CZK in the 46th week of the year.
2. The support for the candidate in the first place will be 1.5 percentage points or higher than the support for the candidate in the second place in the October 2022 Czech presidential election according to the Median presidential election model.
3. Vladimir Putin will still be the incumbent president of the Russian Federation on December 12th at 12:00.
4. The number of patrons of the U kulatého stolu podcast on Patreon will equal 1,750 or more on December 5 at 12:00.
5. One artist will have two or more songs among the top twenty songs on the Billboard Hot 100 chart for the week of October 30 to November 5.
6. The price of the Ethereum cryptocurrency will not exceed 2,200 USD per ETH token at any point between October 18 and December 13.
7. The University of Economics will have four or more projects supported among the standard projects of the Grant Agency of the Czech Republic starting in 2023.
8. The number of PCR tests conducted on December 5 will be less than 11,000.
9. There will not be a demonstration with an estimated attendance of 70,000 or more on Wenceslas Square in November.
10. The winner of the 101st President of the Republic Prize marathon in Chuchle will have a time of 3:35:00 or more.
11. At least four European countries will make it to the quarterfinals of the 2022 FIFA World Cup in Qatar.
12. The price of Natural 95 gasoline at the EuroOil gas station on Rajská Street in Prague will be 44.50 CZK or higher on December 1 at 13:00.
13. The EUR/CZK exchange rate will not be 24.6 or higher on December 2.
14. The temperature in Prague will drop below -10 °C at some point in January 2024.
15. The number of daily new COVID-19 cases in the Czech Republic will be less than 1,000 on May 1, 2023.
16. The number of electric vehicles registered in the Czech Republic will be more than 50,000 by the end of 2023.
17. The Czech men's national basketball team will not qualify for the 2024 Olympic Games in Paris.
18. The number of foreign tourists visiting the Czech Republic in 2023 will be at least 75% of the number of visitors in 2019.
19. The price of gold per ounce will be higher on December 31, 2023, than it was on April 3, 2023.
20. The number of people employed in the Czech Republic in the fourth quarter of 2023 will be higher than the number employed in the fourth quarter of 2022.

Data availability

Data will be made available on request.

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