PRÁTICAS EM CONTABILIDADE E GESTÃO ISSN 2319-0485 e14625

COMBINED FORECAST: EFFECT OF AMPLITUDE OF DATA VARIATION AND CONTEXT FRAMING ON THE ANCHORING POINT IN FORECASTING

PREVISÃO COMBINADA: EFEITO DA AMPLITUDE DE VARIAÇÃO DE DADOS E ENQUADRAMENTO DE CONTEXTO NO PONTO DE ANCORAGEM EM PREVISÕES

Received in 7.11.2021
Approved in 9.15.2021

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RESUMO

Não há dúvidas sobre a importância dos modelos quantitativos de previsão na gestão. Entretanto, em contextos incertos, os modelos matemáticos estabelecidos devem ser ajustados, já que as variáveis e parâmetros podem sofrer alterações em relação ao momento da concepção. Considerando esse fato, os julgamentos humanos são necessários em atividades de previsão. Porém, sabe-se que os tomadores de decisão são limitados racionalmente, portanto, devem recorrer à heurística para simplificar certas decisões. Este estudo busca investigar como a amplitude da variação da demanda histórica e o enquadramento de ganho/perda do contexto podem afastar a decisão do ponto de ancoragem da previsão. Metodologicamente, empregamos o experimento controlado e analisamos a data usando regressão *ordinary least square*. Nossos resultados demonstraram que a amplitude de variação poderia influenciar negativamente o desvio em torno do ponto de ancoragem e nenhum efeito estatístico do enquadramento do contexto de negócios foi notado. Gerencialmente, contribuímos chamando a atenção dos gestores sobre possível viés nas decisões e métodos como evitá-los.

PALAVRA-CHAVE

Heurística, ponto de ancoragem, experimento controlado, enquadramento ganho/perda, fator humano.

ABSTRACT

There is no doubt about the importance of quantitative forecasting models in management. However, in uncertain scenarios, established mathematical models should be adjusted, since variables and parameters might have changed compared to the original models. By considering this fact, human judgments are required in forecasting. However, it is known that decision-makers are bounded rationally, hence, they employ heuristics to simplify certain decision-making. Our study aims to investigate how the amplitude of variation of historical demand and the gain/loss framing of business context could drive decision-makers away from the forecasting anchoring point. Methodologically, we employed controlled experiment and analyzed the data using ordinary least square regression. Our results demonstrated that amplitude of variation could negatively influence the deviation around the anchoring point and no statistical effect of the business context framing was noted. Managerially, we contributed by reminding the managers about the possible bias in their judgment and methods to avoid it. The detailed discussion could be found in the manuscript.

KEYWORDS

Judgmental forecasting. Heuristic. Anchoring point. Controlled experiment. Gain/loss framing.

INTRODUCTION

During the last two years, the business environment has been challenged by the effect of Covid-19. The well-being and mental health of employees were at risk due to a long time of lockdown and home office (NHS, 2020; Singh et al., 2020), supply chain had been disrupted and current business assumptions had been questioned (Helper & Soltas, 2021). In this uncertain period, every manager and policymaker is wondering how the world post-Covid will look like (Cheema-Fox et al., 2020; Contractor, 2021). And from a forecasting perspective, this exceptional condition, variables of established mathematical forecasting models, and their parameters might not be more valid, hence needing adjustment (Lawrence et al., 2006; Lawrence & O'Connor, 1992; Turner, 1990).

The human factor in judgmental forecast is not recent (O'Connor et al., 1993), it is catching the attention of the researchers for a while and there is still a lot to be done in this area (Perera et al., 2019). Human participation in forecasting could be 100%, which means the forecasting is done purely by human judgment or combined, which means human judgment, based on emotion, intuition, heuristics, domain expertise, and value system is used to adjust prediction suggested by mathematical models. In our study, we focused on the latter one.

Concerning the efficacy of judgmental forecasting, there is no consensus about it (Kremer et al., 2011), and we have no ambition to solve it. We aim to find out how the framing of gain/loss and data representation could impact the forecast adjustments around the anchoring point. Our investigation is in line with the research of De Baets and Harvey (2018) and Theocharis and Harvey (2016). However, differently from those studies, we introduced the framing perception in the decision-making. Our study was founded on the concepts of bounded rationality (Simon, 1959), heuristic (Kahneman, 2003), and anchoring (De Martino et al., 2006; Gino & Pisano, 2008; Perera et al., 2019).

Methodologically, we employed a 2 x 2 between-subject vignette experiment to conduct our study. We manipulated the amplitude of the variation of the historical dataset and the gain/loss framing of the business context. From our results, we noted that large amplitude variation of the historical dataset led the respondents to attach more to the

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anchoring point. Meanwhile, we found no statistical effect of the gain/loss framing of business context.

To organize the document, our manuscript is structured in the following sections: "Theoretical foundation"; "Methodology"; "Results and discussions", and "Final considerations".

THEORETICAL FOUNDATION

In this section, we discuss the core concept of few quantitative forecasting methods. Then, we contrast it with judgmental forecast and, finally, build our hypotheses. The idea of our study is not to discuss technically the forecasting models, but how behaviors interplay with the objective information.

Quantitative forecasting

According to Heizer et al., (2021), forecasting could be divided into qualitative and quantitative methods. The former involves the decision-maker's emotion, intuition, expertise, and value system and it is more subjective and judgmental. Meanwhile, the latter is based on mathematical models, and it is extremely objective.

According to Georgoff & Murdick (1986), quantitative forecasting could mainly be divided into time series and association or causal methods. The core concept of the time series model is to predict the future based on patterns of historical data that are evenly spaced in time. Among numerous methods, one way to analyze the time series is through decomposition of historical data in trend, seasonal, and irregular components (Harvey, 1984). This method is used to forecast the tourist flow to Barbados and Hong Kong (Jackman & Greenidge, 2010; Song et al., 2011); Dilaver and Hunt (2011) employed it to predict the industrial energy's demand in Turkey.

Another popular method to analyze time series is the moving average (Georgoff & Murdick, 1986). This technique suggests that the forecast of the current period is given by the average of the *n* most recent period of the historical dataset before the current period. Due to its simplicity, it is largely employed. For instance, the Brazilian media

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consortium uses this method to calculate the progression of decease due to Covid-19 (Marins et al., 2021, July 7). Moving average assumes that all the historical data point has the same weight, however, it is possible to add greater weight to a more recent data points (Heizer et al., 2021). There are also other more advanced methods incorporating moving average such as autoregressive integrative moving average (Arima) (Harvey, 1984; Lee & Fambro, 1999), or Arima integrated to genetic programming (Lee & Tong, 2011) or season moving averagely integrated to the artificial neural network to improve the accuracy of prevision (Barrow, 2016).

Time series could also be analyzed by exponential smoothing (Georgoff & Murdick, 1986), which is a variation of the moving average (Heizer et al., 2021). This method suggests that the new prediction is calculated by the previous prediction plus the error of the previous prediction multiplied by a factor (smoothing constant). This method gained visibility thanks to the publication of Gardner (1985), and it also proposes a mathematical model with a trend and a seasonal component (Billah et al., 2006; De Gooijer & Hyndman, 2006; Hyndman et al., 2002). For instance, Tratar et al., (2016) improved the exponential smoothing method and applied it to the demand forecast; Rendon-Sanchez and Menezes (2019) advanced the method by combining it to the structural model and applied it in the forecast of the electricity and load demand; Oliveira and Oliveira (2018) also employed a variation of the exponential smoothing to forecast the electricity demand for seven countries, including Brazil.

Besides those methods previously mentioned, there are other quantitative methods, such as correlational, regression, and econometric models. In our literature review, we are not going to discuss each of them, since these methods are extremely popular and numerous books and articles present them in a didactical way (Hair et al., 2014; Sweeney et al., 2013).

Judgmental and quantitative forecasting

Judgmental forecasting is the adjustment executed by decision-makers on the forecast done by software or quantitative methods (Lawrence et al., 2006; Lawrence & O'Connor,

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1992). Fischhoff (1988) advocated that quantitative and judgmental forecasting are complementary. According to Turner (1990), the adoption of judgmental adjustment is necessary to improve the quantitative forecast model, since some variables from the forecasting model could change during the studied period, hence, statistically impossible to estimate. Moreover, changes in external factors could cause structural change which has not been incorporated by the model. For instance, Cerullo and Avila (1975) noted that, from their 110 surveyed companies, 89% of their sample used only judgemental method or judgments along with other methods; Lawson (1981) stated that judgments were used to correct or to adjust and improve the quantitative forecast of phone traffic; Onkal et al (2008) noted that employing judgmental adjustment could improve the accuracy of the forecast; Edmundson et al., (1988) and Huang (2012) observed that a well structured judgemental process could be consistently more efficient than the traditional quantitative method; and more recent study also demonstrated that combination of quantitative forecast model with judgmental adjustment could outperform only qualitative or quantitative method (Salehzadeh et al., 2020).

However, Kremer et al. (2011) suggested that the performance of judgmental forecasting is not a consensus. Bunn and Wright (1991) observed that the benefit of judgemental adjustment on extrapolation method with modified variable was very little. Carbone et al., (1983) conducted an intervention study with students and proved that judgemental adjustments did not improve the accuracy. Fildes et al., (2009) noted that judgment adjustment could increase the accuracy in the supply chain, however, it could incur bias as well. Lawrence et al., (2006) suggested that there are necessary conditions to adopt judgmental forecasts, such as ensuring technical knowledge of the forecaster, provide feedback on the accuracy of the forecast, or decompose forecasting tasks to smaller ones for the decision-makers.

Complementing the remarks raised by Lawrence et al. (2006), the judgmental forecast is subject to bounded rationality and heuristics, which is rational decision-making based on easily processed information (Kahneman, 2003).

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Hypothesis development

According to Simon (1959), the cognitive capacity of humans is limited, what leads to bounded rationality and, due to this limitation, the decision-makers adopt heuristics (Gino & Pisano, 2008; Kahneman, 2003). Lawrence and O'Connor (1992) tested and observed the effect of the source of few heuristics in forecasting, such as series length presented, recency of the historical data, and anchoring. Afterward, Lawrence et al. (2006) observed other issues that impact the heuristics in the judgmental forecast, such as the domain of forecast or expertise of the decision-makers.

Harvey and Reimers (2013) advocated that individuals tend to anchor to the last point of the time series and try to adjust to the average of the trend. Later, Theocharis and Harvey (2016) noted that end-anchoring increased the accuracy of the forecast for the more distant horizon. And De Baets and Harvey (2018) noted that the forecast, initially, is anchored on the average of the data series, however, decision-makers tend to adjust away from this anchor for future forecasts, and the over/under forecast were impacted by the sporadic perturbation, such as promotion.

In addition to the effect of anchoring, Lawrence and O'Connor (1992) suggested that the forecast errors could be negatively related to the size of the representation scale. This effect is also known as the impact of representation, and according to Perera et al. (2019), there is no consensus about the best way to visually present the dataset. Due to this lack of consensus about the data presentation, Remus (1984) had suggested that tabular representation might be more suitable for low complexity and graphical for intermediate complexity datasets. Later, Bendoly (2016) proposed a series of best practices in data representation.

By considering the previous rationale, we assume that individuals will start their forecast from an anchoring point, such as a number suggested by the forecast system. In addition, given that the representation of the scale of the dataset could influence the judgment forecasting, therefore, we expect that how we describe the amplitude of the variation of our dataset and its graphical representation could impact how decisions of the individuals will deviate from the anchoring point. Given that a larger amplitude of variation of the dataset is related to higher uncertainty, we expect that individuals would

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behave in a more risk-averse fashion and would attach more to the anchoring point than a smaller amplitude variation of the dataset. Hence, we propose:

- Hypothesis 1: The larger the amplitude of the variation of the historical dataset, the less will the decision-maker deviate from the suggested quantity (anchoring point).

According to Kahneman (2003), the context could also influence how individuals decide. They advocated that, in a rational decision process, individuals would weigh the value of the loss and the gain, however, the loss tends to have a larger weight. In this process, the value perception is reference-dependent, which means that the effect of the current stimulus will depend on the context and the effect of the previous stimulus. For instance, selecting or not a supplier that presents a 50% of probability of behaving opportunistically (making you lose US$ 100,000.00) and a 50% of probability of cooperating with you (increasing your revenue by US$ 150,000.00)? Will this choice change if the overall revenue is reduced by US$ 100,000.00?

Another point regarding the context is related to how individuals frame it. The framing effect is associated with how the description of the context could lead individuals to different choices (Berger & Janoff-Bulman, 2006; De Martino et al., 2006; Kahneman & Tversky, 1979). For instance, in the famous case of a cup that is 50% filled up, we could frame it as 50% full or 50% empty.

From this reasoning, we expect that how individuals frame a managerial situation could impact forecasting. According to the prospect theory (Kahneman, 2003), the negative utility associated with loss increases faster than the positive utility associated with the gain. Therefore, we expect that, in a situation in which the context is framed as losing money, the individuals will tend to be more loss-averse, hence, less willing to take risk in an uncertain condition (Charness et al., 2013; Ding et al., 2010; Donthu & Gilliland, 1996; Griffin et al., 1996). Consequently, in a forecasting situation, we expect that:

- Hypothesis 2: Under the effect of the loss framing (losing money), the decision-maker will deviate less from the suggested quantity (anchoring point).

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METHODOLOGY

Controlled experiment design and procedure

We employed a vignette-based experiment (Rungtusanatham et al., 2011). Our experiment was a 2 x 2 between-subject, in which we manipulated the amplitude of the variation of the demand (large/small) and framing of the business condition (gain/loss). Before data collecting, the scenarios were shown to managers and academics researchers to gather their opinions and improve the realism of our scenarios. And we also pre-tested our scenarios to assure a good understanding of their content.

In our vignettes, the respondents assumed the role of a purchasing agent, in which they had to estimate the number of clothes to purchase for the following season, which will start in eight months (for more detail, see Appendix I). The small amplitude of variation is described as a uniform distribution that will vary between 1000 to 5,000 pieces and a large amplitude between zero to 20,000 pieces. For the gain framing, the scenario described that those items not sold during the season are sold later with a discounted price, hence recovering a certain amount of the investment. On the other hand, for loss framing, those non-sold items that were sold later at a discount price were described as losing a certain amount of the investment.

The main task of our respondents is to define how many pieces of garment to buy for next season. To execute this task, we gave the respondents of each scenario an anchor point, which is approximately the average of the uniform distribution. The small-amplitude variation is 3,000 units, and the large variation is 10,000 units. We told the respondents that this suggestion is given by the system.

Our subjects were recruited from Amazon Mechanical Turk, and we paid US$ 1.00 to each participant. Amazon Mechanical Turk is considered a cheap and reliable source for controlled experiments, even for studies concerning organizational and business topics (Buhrmester et al., 2011; Lee et al., 2018; Paolacci et al., 2010). Concerning the subject pool, it is important to remark that the controlled experiment is not to test how experimental settings are close to typical organizational context, but the controlled

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experiment is to test the theory underneath the organizational phenomenon through reliable variables (Highhouse, 2009). According to Lonati et al. (2018), results obtained in a controlled experiment should not be interpreted quantitatively, but from the sign (positive or negative causal relationship between variables) and effect (existent or not), which should be the main concerns. In their discussion, they drew a parallel between the business-controlled experiment to the airplane model tested in the wind tunnel.

Once the subjects from Amazon Mturk Mechanical Turk accepted to take part in our study, they were forwarded to the Qualtrics platform, where the actual study was hosted. When the respondents arrived at our website, the instruction told them that they could leave the study at any time and at any point. They were aware that our study is confidential, anonymous and it implies no risks. In our experiment, we randomly allocated the respondents to one of the four scenarios. From the data collected, we remove those duplicated IP addresses to remove possible impostor respondents (Dennis et al., 2019). To improve the quality of our subject pool, we set the HIT (Human Intelligence Task) approval rate of the participants to 95%, where each HIT represents a job completed by the respondent in Amazon Mturk. The higher the approval rate, the more jobs of the participant were approved, hence higher their quality (Nichols et al., 2019). In our study, we also checked the effectiveness of our manipulation, the risk propensity of our respondents, their demographic background, and the realism of our vignettes.

VARIABLES

Dependent variable

In our experiment, we worked with the idea of aggrege planning where the planning of demand is at the family level. The respondents defined the number of pieces of clothes to order for the next season. The quantity defined to be purchased could vary from 0 to 30 K units. As we offered the respondents the anchor point, we are interested in how our respondents deviate from the suggested quantity.

Since there is one anchor point for small and one for large variation, we standardized the difference of the order quantity to the anchor point for each scenario.

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Independent variables and control variables

The main two independent variables are those manipulated ones. The first one is the amplitude of the variation (small/large), and we used the dummy variables to code it (small: 0; large: 1). The second independent variable is the framing (gain/loss), and we also dummy code it (gain: 1, loss: 0).

In addition to our two main independent variables, we adopted few control variables. Since our study involves decision in uncertainty situation, therefore, first, we controlled the risk propensity of the subjects (Sitkin & Weingart, 1995). To measure the risk-propensity, we divided it in two dimensions: risk-taking and averse, each, using 3 questions of 7-points scale where the higher the more intense is the respective propensity (Charness et al., 2013; Ding et al., 2010; Donthu & Gilliland, 1996; Griffin et al., 1996) – See appendix. We also controlled the time perception of the respondents with a question where we measured how soon the respondents perceived the next season which will start in 8 months. We used a 7-point scale where the higher, the sooner is the time perception. Finally, we controlled the demographic variables: age and gender.

Variable reliability and manipulation check

To check the reliability of our variables we followed the recommendation of Ringle et al. (2015) and employed SmartPLS 3.0. To assess the effectiveness of the manipulation of the amplitude of demand variation, we must be sure that the small and large variations of the demand are equally difficult to predict. We used three questions of 7-point scales – how variable, how certain and how predictable is the demand. We found no statistical difference for respondents of small and large variation amplitude; therefore, we could infer that the respondents perceived the demand are equally variable and be sure that the effect is due to the representation of the range presented.

For the gain and loss framing effect, we asked how beneficial is to have the leftover from the season selling. We measured it using a 7-point scale where the higher, the more beneficial it is. From our results, respondents that read gain framing perceived having leftovers as more beneficial than those who read loss framing (M_{gain} = 5.07; M_{loss} = 4.34; p-value = 0.08).

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In terms of the realism of the scenario, in a scale from one to seven – according to which the higher the score, the more realistic it is –, the average for this measurement is 5.82 ± 1.11 from the respondents, hence we know that the scenario was adequate (Rungtusanatham et al., 2011).

For the variables of risk propensity – risk-taking and risk-averse –, these two variables are composed of three items. Risk-taking item's loading ranged from 0.692 to 0.955 and risk-averse item's loading ranged from 0.664 to 0.971. Both variables present Cronbach's alpha above 0.7; composite reliability of 0.858 and 0.872; average variance extracted (AVE) of 0.672 and 0.699 (Hair et al., 2014; Kline, 2015).

RESULTS AND DISCUSSION

We collected 133 responses. 59 of the respondents were female, 72, male and two preferred not to answer this question. The age of our respondents is 35.92 ± 13.24 years old. By removing those inconsistent answers, we had 128 complete answers. Our respondents perceived that 8 months are not far away nor close (4.35 ± 1.40) on a scale of 1 to 7, where the higher, the further.

To assess our hypotheses, we used SmartPLS 3.0 to test the relationships and we adopted the variation from the anchor point as our dependent variable. We started by regressing the dependent on the demographic variables (gender and age). Then, we included the variables of risk propensity (risk-taking and aversion) and time perception. At last, we included the amplitude of variation and framing effect.

From the results of Table 1, we could see that the only significant coefficient is related to our first manipulated variable (amplitude of variation). The negative coefficient indicates that, under the effect of large amplitude of variation, less respondents will deviate from the anchor point when compared to the small amplitude of variation. It is interesting to note that despite both groups (small/large variation amplitude) perceived that future demand is equally difficult to predict, by presenting wider variation, the respondents tend to anchor more to the suggested value, which is evidence of the decision heuristic (Gino & Pisano, 2008; Kahneman, 2003). This result is in line with previous studies (De Baets & Harvey, 2018; Theocharis & Harvey, 2016), according to which the decision-makers tend to anchor to the

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proposed number, and this attachment could be impacted in relation to the behavioral issues. It is also important to remind that, contrary to the common sense belief that heuristic is associated with irrationality, this decision-making is a rational process based on easily-recalled features to help the decision-makers to decide quickly (Kahneman, 2003).

By analyzing the coefficient associated with the framing effect, we noted that it is not significant, hence not supporting our hypothesis 2, according to which we expected that individuals from gain framing could behave in a less loss-averse fashion since they would deviate more from the anchoring point. Despite our hypothesis 2 wasn't supported, it is in line with De Martino et al. (2006), where they observed that in the game framing, subjects tend to gamble less than loss framing. By considering that purchase is a task that involves monetary analysis, our respondents that read the gain framing scenario disregarded the perception of the benefits of the leftover and focus on the rationality side of the task. They behaved similarly to those respondents that were stimulated by loss framing. This result could be attributed to the rational nature of purchasing since existing studies advocated that decision-making in purchasing is a highly rational task (Kaufmann et al., 2012; Kaufmann & Carter, 2006).

Table 1 – Results of the regression for hypothesis assessment

DV: Ddeviation from the anchor point	Model 1	Model 2	Model 3
Age	0.029	0.048	0.074
Gender	-0.047	-0.097	-0.108
Risk-Averse		-0.145	-0.145
Risk-Taking		0.087	0.083
Time Perception		0.033	0.025
Amplitude of Variation			-0.172**
Gain/Loss Framing			-0.098
R2	0.003	0.035	0.070

P-value *** < 0.001; ** < 0.05; * < 0.1

Amplitude of variation (0=small; 1=large); Gain/Loss framing (0=loss; 1=gain)

Source: Elaborated by the authors.

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Moreover, while looking at the results of the non-significant coefficient related to the framing effect, one might wonder whether there is a difference in the risk propensity of respondents from these two groups. We executed the ANOVA Anova) test, and no differences were found. This absence of difference in risk propensity is expected, hence the respondents were randomly assigned in our scenarios. In addition, we also checked if our results could be caused by the unreliability of the quantity suggested by the system (the anchor point). For this purpose, we measured using the seven-point scale, how dependable and trustworthy is that suggested quantity (anchor point), and the respective average is $M_{dependable} = 4.56 \pm 1.33$ and $M_{trustworthy} = 4.66 \pm 1.41$. From these measurements, we inferred that they are neutral regarding the suggestion, and combined with our results of Table 1, we could infer that the deviation from the suggested quantity (anchor point) is due to the adjustment of this value caused by our manipulations.

FINAL CONSIDERATIONS

In our exploratory study, we investigated heuristics in decision-making for forecasting and we followed the same line of Kremer et al. (2011) who investigated how the adjustment forecast deviates from the normative prediction. Like their study, we employed a controlled experiment as the research strategy, however, we focused on the deviation to the anchoring point effect instead of the normative prediction.

We are in line with behavior operations (Bendoly et al., 2006; Gino & Pisano, 2008; Katsikopoulos & Gigerenzer, 2013)or simply behavioral operations (BOps and based on the concept of heuristic decision making (Kahneman, 2003). By assuming that the respondents should quickly make their decisions, we hypothesized that the amplitude of the variation of the historical dataset and the framing of the context could influence the judgment forecasting by deviating the forecasting from the anchoring point.

Our results demonstrated that forecasting in purchasing is an extremely rational task. The monetary analysis could induce the respondents to realize that, despite the positive perception of the leftover due to the gain contextual framing, it is not worthy to assume risky decision or gambling, hence more loss averse. In addition, our results indicate that the judgmental adjustment around the anchor point could be influenced by

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how the historical data was presented to the decision-maker. We noted that when the historical data was presented as a larger amplitude of variation, the respondents anchored more to the suggested quantity, despite the small and large variations followed the same statistical distribution and they are equally difficult to predict the future. From this finding, we could infer that decision-makers adopt heuristics (Kahneman, 2003) to judgmentally adjust the forecast when future conditions are uncertain and cognitively demanding.

The managerial and theoretical implication

Managerially, we know that presenting the historical data in a graphical layout could illustrate a certain pattern of the numbers, and it is extremely important for data analysis (Hair et al., 2014), however, we would like to call the attention of the practitioners to the way how the information is presented to the decision-maker, since, by describing the amplitude of the variation, our study succeed to make decision-makers to anchor more or less on the suggested value. In addition, we also recommend managers, in case of judgmental forecast adjustment, the collection of some opinions from the peers to avoid eventual bias or decomposing the decisional task into smaller tasks (Carter et al., 2007; Hada et al., 2013; Kaufmann et al., 2010).

Theoretically, our research demonstrated that heuristics are applied in the judgmental forecasting adjustment, hence contributing to the discussion in the area of behavioral operations (Gino & Pisano, 2008; Katsikopoulos & Gigerenzer, 2013), which is still under development (Bendoly et al., 2006; Petropoulos et al., 2018; Zhao et al., 2013); and by using a controlled experiment, we could claim causal effects (Antonakis et al., 2010; Lonati et al., 2018; Rungtusanatham et al., 2011). We demonstrated the effect of the anchoring point and how we could influence the decision-makers regarding this point.

Limitation and future studies

By employing control experiments as research strategy, there are inherent limitations due to this methodology. In our experiment, we manipulated the way historical data was

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presented, and we framed the decision context. These manipulations established the causality of the phenomenon we investigated; however, it should be generalized with parsimony. We did not explore how other behavioral aspects could deviate the forecasting from the anchor point, which also consists of potential issues to be investigated (Perera et al., 2019). For instance, in judgmental forecasting, it is recurrent to adopt experts' opinions as input of the decision-making, hence we propose that future studies could investigate how this practice could change the predictions proposed by the mathematical models.

According to Feng et al., (2011), the cultural issue could play an important role in forecast decision-making. According to them, Chinese decision makers, based on the doctrine of the mean, they tend to find the average of a trend a good starting point for forecasting, hence, we suggest that the future study studies investigate whether these cultural particularities could impact judgmental forecasting.

Finally, in our study, we adopted the moving average of three periods to design our scenario, what implies a certain forecast error that the respondents could note in the study. Therefore, we suggest future studies to investigate whether the techniques of the forecast, the representation of the forecast error, or the nature of the product to be purchased could impact the judgmental forecast.

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