BIAS-DRIVEN INVESTING IN EMERGING CAPITAL MARKETS: A BLUEPRINT BASED ON FAMILIARITY, ANCHORING, AND RECENCY

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Abstract: *Behavioral finance serves as an essential method for illustrating how mindset and perception shape investment choices since conventional wisdom on capital market operations logically and insufficiently captures the reasons behind investors' sometimes irrational actions. This paper aims to explore investor behavior across two emerging stock markets, Romania and Turkey, affected by anchoring, familiarity, and recency biases over the last five years, framed by major shifts in the global environment. Average prices of benchmark stock market indices, intercorrelated with the COVID-19 crisis and the Russian-Ukrainian conflict, form the basis of the data in the study. The framework uncovers the effects of psychological variables on stock markets as coefficients and statistical significance tests. The findings reveal meaningful differences between the two capital markets: in post-pandemic Turkey, the negative familiarity index alerts investors' growing knowledge of the stock market, driven by an inflated sense of confidence about it. The anchoring effect in the Romanian post-COVID era has a notable positive impact on prices, implying a more pronounced attenuation in choice-making tied to previous experiences. In contrast, the presence of anchoring bias within the Turkish market has a substantial influence that leads to more rational investment decisions. Recency bias exerts a weaker influence in Romania than in Turkey. The paper highlights the behavioral variations between the markets studied and recommends more studies to clarify the emerging market's mechanisms.*

Key words: *behavioral finance, emerging capital markets, familiarity bias, anchoring bias, recency bias.*

JEL: D91, F37, G41.

1. Introduction

Thaler (1999) argues that the controversy over behavioral finance is fading as researchers recognize the validity of this approach, which integrates systematic investor behaviors and errors into financial models. Ricciardi and Simon (2000) explore the impact of cognitive and emotional factors on decision-making, and important notions include overconfidence, cognitive dissonance, regret theory, and prospect theory. Ritter (2003) argues that behavioral finance elevates the traditional assumption of utility-maximizing rational investors in an efficient market to translate speculative bubbles in the market. Statman (2014) pursues the integration of elements from classical finance into behavioral finance, starting with behavioral portfolio theory and behavioral asset pricing models. Chang (2025) builds a conceptual model based on equational structure analysis to examine the relationship between cognitive/emotional biases and the mood effect in financial behavior. The study explores the impact of behavioral factors such as herd effect, mood effect, blue-chip equity bias, and overconfidence on risk perception and financial literacy, distorting investment decisions (Almansour et al., 2025).
According to Cao et al. (2003), investors avoid unfamiliar options for fear of change, preferring familiar choices, leading to behaviors such as lack of diversification and preference for local or already owned stocks. Bulipopova et al. (2014) demonstrate in an experiment that investors exhibit greater reluctance to take losses when managing familiar assets, creating a doubling of the willingness to hold loss-making stocks. This behavior manifests as familiarity bias that amplifies the disposition effect. In 2018, Liu et al. show in their paper that foreign investors exhibit familiarity bias behavior by being on the list of favorites of emerging markets they are familiar with, thus minimizing the potential for efficient international diversification with these suboptimal investment choices. Dong et al. (2021) edify the negative influence of familiarity bias in earnings-based stock valuation. Lei and

Mathers (2024) discuss investment decision bias, where investors tend to choose familiar or owned stocks, which is influenced by education, income, gender, age, and risk tolerance.
Tlili et al. (2023) explores investment behaviors and the impact of psychological factors in MENA equity markets, highlighting herding and anchoring biases that shape investors' decisions, especially during market downturns. Owusu and Layrea, in 2023, start a study showing that Ghanaian investors are significantly influenced by mental anchoring when it comes to mutual fund investment decision-making. Nguyen's (2024) study shows that large language models (LLMs), including GPT-4 and Claude 2, are affected by anchoring bias in predictions. The study by Sumantri et al. (2024) analyzes the effects of representativeness, availability, and anchoring on investment decisions, finding that representativeness and availability significantly influence these decisions, while anchoring has no significant effect.
Recency bias partially explains the volatility of the US stock market before and after the global financial crisis in the formation of investors' dividend expectations (Gandré, 2020). According to Durand, Patterson, and Shank (2021), NFL bettors are under the influence of recency bias, betting on teams that have won recently, thus creating a chain of irrational decisions exploited by bookmakers. Open-source visual-linguistic models are under attack by recency bias, marking human cognitive biases and extrapolating concerns about their applicability in critical domains (Xiao et al., 2024). Kotomin and Varma (2025) discuss how individual investors reduce their recency bias in December, when, for tax reasons, they evaluate all previous losses in their portfolio and no longer limit themselves to recently purchased securities.
This paper is arranged as follows. Part 2 delineates the methodology applied to fulfill the objectives of this study, specifying the techniques utilized in modeling the three independent variables: familiarity, anchoring, and recency. Part 3 underlines the empirical findings and examines the ramifications of these behavioral characteristics on market price kinematics. The last part summarizes the main insights of investment behavior under the pressure of cognitive errors.

2. Modelling independent variables: familiarity, anchoring, and recency.

The motivation of this paper is to analyze the behavioral factors that explain the fluctuations in transaction prices in two emerging stock markets, Romania and Turkey. The intention is to trace the impact of investors who are characterized by behavioral errors, as independent variables, on the average trading price, as a dependent variable. The time corridor analyzed covers the last five years, from March 2020 to October 2024, covering two of the significant events of the last years, namely, the beginning of the COVID-19 pandemic and the beginning of the war in Ukraine, fueled by global inflation, and incorporates the daily values of the most important stock market indices traded in both markets, namely BET for Romania and BIST 100 for Turkey, together with the daily trading price of the two indices.
During the five years of the study, we have surveyed the impact of two global events, namely the COVID-19 pandemic (March 11, 2020– February 23, 2022) and the war in Ukraine, along with global inflation (starting February 24, 2022), on stock markets, highlighting the effects on global economies and market volatility. We have selected a quarterly analysis, dividing these events into four-month periods to highlight market developments and the effects of each crisis on investor behavior and trading volume.
The bias exposure of investment behavior makes its modeling a complex one, treated in a psychological manner. The proposed model combines familiarity bias, anchoring effect, and recency bias in processing the average trading price.
The anchoring of the investor in the first information offered in the market makes his investment decision disproportionately influenced by that initial reference point; thus, the decision process is prone to cognitive errors on the background of over-reporting.
In highlighting the anchoring effect, we relied on the following hypothesis: if the current price in the market is higher than the price at the time of the event trigger or anchor price, i.e., for the pandemic,

March 11, 2020, and for the war in Ukraine, February 24, 2024, then investors remain anchored to the initial price and do not open investment positions in the stock market; the investor tends to avoid the investment, perceiving it as a favorable opportunity already lost, not perceiving it as a real growth opportunity in the future.
The investor's likelihood of investing decreases as the current price is further away from the reference price. The mental anchor causes any change in the market to be seen by the investor as below the initial one.

$$\begin{cases} if\ Pt > Pa, there\ will\ be\ no\ trading = anchoring\ effect\ inactive. \\ if\ Pt < Pa, there\ will\ be\ trading = anchoring\ effect\ active. \\ Anchoring\ index = average\ (population\ of\ anchors). \end{cases} \quad (1)$$

The familiarity bias refers to the investor's tendency to opt for investments considered safe for him, familiar, in the absence of his preference to invest in unfamiliar securities or to go out of his comfort zone.
In considering the quantification of the investor's familiarity index as inversely proportional to price volatility, we considered that an asset with low price volatility denotes stability, hence familiarity. Exponential familiarity increases investment probability, even when returns are not exceptional. Investors prefer investing in the familiar because it gives them a sense of security and control; even if the assets have the same real risk, the investor perceives the familiar asset as less risky.

$$\begin{cases} if\ volatility\ increases, the\ familiarity\ index\ decreases. \\ if\ volatility\ decreases, the\ familiarity\ index\ increases. \\ Familiarity\ index = 1/volatility. \end{cases} \quad (2)$$

Recency bias is perceived to be a cognitive error whereby people attach greater importance to recent events compared to those in the distant past; thus, recent information is incorporated into the price, whether it is relevant or less significant. So, an investor will be influenced by the recency bias when buying an asset just because its price has risen recently, believing that it will continue to rise, or avoiding an asset in the long run because it has had a recent decline. Investors see the recent rise in price as a positive signal, and the recency bias gives them the impression that the trend will continue tomorrow, thus creating a form of FOMO, and traders decide to enter the market while the price is still going up. Unrealistic expectations stimulate optimism and involve the investor in a string of trades.

$$\begin{cases} if\ Pt > Pt-1, there\ will\ be\ trading = recency\ effect\ active. \\ if\ Pt < Pt-1, there\ will\ be\ no\ trading = recency\ effect\ inactive. \\ Recency\ index = average\ (recency\ population). \end{cases} \quad (3)$$

The study has integrated the average price as the dependent variable because it focuses on the market evolution and is influenced by rational expectations and investor behaviors such as familiarity, anchoring, and recency.

$$Price = \beta 0 + \beta 1 * Familiarity\ index + \beta 2 * Recency\ index + \beta 3 * Anchoring\ index.$$

3. Empirical results.
The regression analysis serves to underscore how rational expectations and behavioral biases shape trading activity across the two emerging capital markets under investigation.
Table 1 shows the coefficients of the independent variables for event 1 (the COVID-19 pandemic) for the Romanian and the Turkish capital markets. The results report coefficient, t-statistic, and R^2 values for each variable.

Table 1. Coefficients of independent variables for Event 1 (the COVID-19 pandemic)

Capital market	Independent variables	Coefficients	t-statistic	R-square
Romania	Constant (Average Price)	5.222202594	0.044069345	0.494818773
	Familiarity	-0.211892751	-0.115950768	
	Anchoring	-6.276438583	-0.061106918	
	Recency	2215496292	0.610074458	
Turkey	Constant (Average Price)	208429.2412	9699222921	0.996844033
	Familiarity	-49402.8623	-1.755037469	
	Anchoring	-205567.3721	-8.958257141	
	Recency	-1004.354845	-0.451153941	

Source: Author's contributions

After reading the table, it can be highlighted that in Romania, during the pandemic period, the coefficient for the constant is 5.22, with a t-statistic of 0.044, which denotes a low significance of this term in the model.

The familiarity index is negative, which indicates an inversely proportional relationship between the familiarity of investors and the average price in the market; thus, in the Romanian market, more experienced investors or those more familiar with market developments become more cautious or more reluctant to make significant investments.

The negative anchoring bias suggests that the anchoring effect is also inversely proportional to the average price. In other words, investors do not accept transactions at prices higher than the anchor price, which creates a price decrease due to a conservative attitude of investors in the Roman market.

The recency coefficient is a positive 22.15, accompanied by a t-statistic of 0.610, which marks a significant relationship between recency bias and average price. In other words, investors respond positively to new stimulus, which generates a price increase, where recent information influences investors' perceptions to a quick and positive market reaction.

In the Turkish stock market, a significant negative relationship exists between familiarity and average market price, as shown by the coefficient of familiarity at -49402.86 and the t-statistic at -1.76; as investors become more familiar with the market, prices tend to decrease.

The anchoring effect is at -205567.37, accompanied by a t-statistic of -8.96, which shows a significant influence of anchoring on the average price, where investors rely too much on previous reference prices, thus triggering a decrease in market prices.

The recency error of -1004.35, with a t-statistic of -0.45, indicates a weakly significant negative relationship between the variable "recent" and the average price in the Turkish market. In other words, Turkish market investors do not seem to react much to recent market changes.

In general, the R^2 is much higher for Turkey (0.997) than for Romania (0.495), indicating a higher degree of explicitness for price changes in the case of the Turkish market of behavioral indicators.

Table 2 reports the coefficients of the independent variables, i.e., coefficients, t-statistics, and R^2, for the second event (the Ukraine-Russia war, coinciding with global inflation) on the Romanian and Turkish stock markets.

Table 2. Coefficients of independent variables for Event 2 (the Ukraine-Russia war)

Capital market	Independent variables	Coefficients	t-statistic	R-square
Romania	Constant (Average Price)	14.9012728	2.135070632	0.771567289
	Familiarity	0.115068227	0.343010327	
	Anchoring	4.99097425	3.283484919	
	Recency	-6.905732145	-0.544066614	
Turkey	Constant (Average Price)	17424.176	8651409412	0,939854613
	Familiarity	-1543194.155	-4.93892525	
	Anchoring	0	65535	
	Recency	-13410.1784	-3.627029181	

Source: Author's contributions

On the Romanian market, the dependent variable (average price) indicates a significant relationship with the independent variables in the model, which is a satisfactory explanation of the price variation. The positive familiarity bias of 0.12, with a t-statistic of 0.34, shows a positive relationship between investors' familiarity and the average price.

The anchoring effect of 4.99 with a significant t-statistic of 3.28 signifies a positive and significant anchoring effect on the average price, where investors are influenced by the previous reference prices in the Romanian market.

The recency bias of -6.91, with a t-statistic of -0.54, assigns a weak negative relationship with the average price, where recent events do not seem to impact the prices of the Romanian stock market.

In the Turkish market, during the Russian-Ukrainian war, the familiarity index of -1543194.16, accompanied by a t-statistic of -4.94, suggests a significant negative relationship between familiarity and average price, indicating that higher familiarity could lead to lower prices, a more cautious attitude on the part of investors, or a less favorable reaction to familiar information.

The coefficient of recency bias of -13410.18, with a t-statistic of -3.63, indicates a significant negative influence of the variable on the average price in the Turkish market, which could mean that recent events have a significant negative impact on stock prices.

Overall, with a higher R^2 for Turkey (0.94) than for Romania (0.77), it suggests a better ability of the model to explain price changes in Turkey.

4. Conclusions.

By comparing Romanian and Turkish stock markets between March 2020 and October 2024 to explore how investor behavior was impacted by anchoring, familiarity, and recency biases, we found that the Turkish market model has a higher power to explain the price relationship with these biases. In this market, the recency bias in the Russian-Ukrainian war period shows a significant negative effect on prices, suggesting that recent events negatively influence investors' perceptions and stock prices.

Also, the negative market familiarity index in Turkey in the post-pandemic period suggests a higher investor familiarity with the market, due to overconfidence or overly optimistic market perception.

In the post-pandemic period, the anchoring effect is significantly positive and influences the average price in the Romanian capital market so that investors are more likely to be informationally anchored in their decision-making. In contrast, the Turkish stock market's anchoring coefficient indicates that this factor has no effect on the market, suggesting that investors are more rational and less influenced by external anchors.

Compared to the Turkish market, where recent events or external factors may have a greater impact on market behavior, the Romanian market's recency bias is not as significant.

Finally, the analysis shows that the capital markets in Romania and Turkey behave differently and that each country's stock prices may be impacted differently by behavioral, anchoring, familiarity, or recency variables. I believe that the model explains the evolution of the Turkish market, while further analysis is needed in Romania to clarify the influences of independent variables on prices.

References

1. Thaler, R. H. (1999). The end of behavioral finance. Financial Analysts Journal, 55(6), 12–17. https://doi.org/10.2469/faj.v55.n6.2310
2. Ricciardi, V., & Simon, H. K. (2000). What is behavioral finance? Business, Education & Technology Journal, 2(2), 1–9. https://ssrn.com/abstract=256754
3. Ritter, J. R. (2003). Behavioral finance. Pacific-Basin Finance Journal, 11(4), 429–437. https://doi.org/10.1016/S0927-538X(03)00048-9
4. Statman, M. (2014). Behavioral finance: Finance with normal people. Borsa Istanbul Review, 14(2), 65–73. https://doi.org/10.1016/j.bir.2014.03.001
5. Chang, H.-H. (2025). Application of structural equation modeling in behavioral finance: A study on the disposition effect. In Handbook of Financial Econometrics, Mathematics, Statistics, and Machine Learning (pp. 543–566). World Scientific. https://doi.org/10.1142/9789819809950_0016

6. Almansour, B. Y., Almansour, A. Y., Elkrghli, S., & Shojaei, S. A. (2025). The investment puzzle: Unveiling behavioral finance, risk perception, and financial literacy. Economics, 13(1), 131–151. https://doi.org/10.2478/eoik-2025-0003
7. Cao, H. H., Hirshleifer, D., & Zhang, H. H. (2003). Fear of the unknown: The effects of familiarity on financial decisions (Preliminary version). Retrieved from https://papers.ssrn.com/sol3/papers.cfm?abstract_id=460660
8. Bulipopova, E., Zhdanov, V., & Simonov, A. (2014). Do investors hold that they know? Impact of familiarity bias on investor's reluctance to realize losses: Experimental approach. Finance Research Letters, 11(4), 463–469. https://doi.org/10.1016/j.frl.2014.10.003
9. Liu, Y., Park, J. L., & Sohn, B. (2018). Foreign investment in emerging markets: International diversification or familiarity bias? Emerging Markets Finance and Trade, 54(10), 2169–2191. https://doi.org/10.1080/1540496X.2017.1369403
10. Dong, Y., Young, D., & Zhang, Y. (2021). Familiarity bias and earnings-based equity valuation. Review of Quantitative Finance and Accounting, 57, 795–818. https://doi.org/10.1007/s11156-020-00949-y
11. Lei, S., & Mathers, A. M. (2024). Familiarity bias in direct stock investment by individual investors. Review of Behavioral Finance, 16(3), 551–579. https://doi.org/10.1108/RBF-03-2023-0074
12. Tlili, F., Chaffai, M., & Medhioub, I. (2023). Investor behavior and psychological effects: Herding and anchoring biases in the MENA region. China Finance Review International, 13(4), 667–681. https://doi.org/10.1108/CFRI-12-2022-0269
13. Owusu, S. P., & Laryea, E. (2023). The impact of anchoring bias on investment decision-making: Evidence from Ghana. Review of Behavioral Finance, 15(5), 729–749. https://doi.org/10.1108/RBF-09-2020-0223
14. YUU8UJ
15. Nguyen, J. K. (2024). Human bias in AI models? Anchoring effects and mitigation strategies in large language models. Journal of Behavioral and Experimental Finance, 43, 100971. https://doi.org/10.1016/j.jbef.2024.100971
16. Sumantri, M. B. A., Susanti, N., & Yanida, P. (2024). Effect of representativeness bias, availability bias and anchoring bias on investment decisions. Economics and Business Quarterly Reviews, 7(2). https://ssrn.com/abstract=4857731
17. Durand, R. B., Patterson, F. M., & Shank, C. A. (2021). Behavioral biases in the NFL gambling market: Overreaction to news and the recency bias. Journal of Behavioral and Experimental Finance, 31, 100522. https://doi.org/10.1016/j.jbef.2021.100522
18. Xiao, Y., Lin, Y., & Chiu, M.-C. (2024). Behavioral bias of vision-language models: A behavioral finance view. arXiv preprint arXiv:2409.15256. https://doi.org/10.48550/arXiv.2409.15256
19. Kotomin, V., & Varma, A. (2025). Debiasing recency: Evidence from individual investor stock sales. Journal of Behavioral Finance. https://doi.org/10.1080/15427560.2025.2485461
20. Gandré, P. (2020). US stock prices and recency-biased learning in the run-up to the Global Financial Crisis and its aftermath. Journal of International Money and Finance, 104, 102165. https://doi.org/10.1016/j.jimonfin.2020.102165
21. Oprean-Stan, C., & Tanasescu, C. (2014). Effects of behavioural finance on emerging capital markets. Procedia Economics and Finance, 15, 10.1016/S2212-5671(14)00645-5. https://ssrn.com/abstract=5085946