Anggaran: Jurnal Publikasi Ekonomi dan Akuntansi
Volume. 3, Nomor. 1, Tahun 2025
e-ISSN : 3031-3384; dan p-ISSN : 3031-3392; Hal. 319-329
DOI: https://doi.org/10.61132/anggaran.v3i1.1240
Available online at: https://journal.areai.or.id/index.php/anggaran

The Impact of Digital Financial Trading on Investor Behavior In Traditional Financial Markets

Haider Abbas abdullah Aljanabi
Collage of Administration & Economics, Kerbala University, Iraq

Address: Karbala, Karbala Governorate, 56001, Iraq
Email korespondensi: haider.abbas@uokerbala.edu.iq

Abstract*. Based on the great development that has included all aspects of life, including financial investment, and with the entry of technology with all its strength in facilitating business, great thought has begun to be given to explaining how technology affects investor behavior when entering the securities market. The research dealt with a digital platform (Trader4) and its impact on attracting investors to invest through it. The results showed that digital platforms have a great impact on investor behavior by providing many services that facilitate work for the investor, which prompted many investors to resort to digital platforms and invest through them and leave traditional markets. This gave indications that digital platforms have changed investor behavior through the attraction factors that they used towards the investor. The research presented a set of recommendations, the most important of which was to work on raising awareness and understanding among investors through the media and publishing on how to choose the right path in building their financial investments and using technology in its forms that help build society financially and investment-wise.*

Keywords*: Technology, Investors, Platforms, Behavior*

1. INTRODUCTION

Digital trading of financial instruments, which now has a significant impact on the behavior of traditional financial markets, has evolved from the first electronic trading platforms that started operating in the mid-1990s. Traders and investors can now easily access digital platforms through the internet from any location at any time, including using their mobile devices. Owing to technological developments or regulatory amendments, such digital platforms tend to operate as broker-operated facilities that allow customers to intermediate orders directly with market makers in the relevant financial instruments. Therefore, from the perspective of valuing digital equity platforms, one has to deal with how the services they offer may change the interaction of various types of trading investors active in liquid financial equity markets. The project aims to examine the extent to which digital trading can transform investor behavior in auction markets for financial assets by examining the interactions between digital and transaction costs and pricing in investment strategies and the asset markets in which such strategies are executed. Our research questions underlying this study include: 1. Are there structural differences in the way traditional active investors and digital investors trade? 2. Given these differences, how does the introduction of such digital platforms, with their low costs of digital trading, affect the optimal control, execution, and risk management of the active non-digital investors? 3. Can these insights provide a measure of the extent of transformation that may occur in the trading behavior and

Received: Desember 23, 2024; Revised: Januari 07, 2025; Accepted: Januari 29, 2025;
Online Available: Januari 30, 2025

pricing of the digital and non-digital investors in the digital platforms? We use a three-period stochastic, incomplete-market asset pricing model to provide some initial insights into these questions. We then consider a model in which the digital platforms are run by dealers acting as market intermediaries using complete-subsets pricing and clarify the structural differences that arise when we highlight the issues of control, timing of transactions, and the impact of transaction costs in the three periods of the back-to-back trades. By examining these factors, we aim to gain a deeper understanding of how digital trading platforms can reshape the behavior and strategies of investors in both digital and non-digital environments. Ultimately, our findings will contribute to the ongoing discourse surrounding the impact of digitalization on financial markets and inform policymakers, investors, and market participants on the potential implications and opportunities associated with this transformation. (Javaid, 2024) (King & Koutmos, 2021).

2. LITERATURE REVIEW

The objective of this paper is to investigate the direct and indirect influence of digital trading on investor behavior in traditional financial markets. The following section presents a review of the literature that addresses this theme. Technology, especially in the form of digital platforms and trading, is a trending topic in today's economy. Businesses and services have been digitalized for some time, and digital trading is increasingly complementing more traditional forms of brokerage. While several authors argue and study the changes and implications for companies moving to digital offerings of their services, few papers address the consequences of such an evolution for the customer, be it private or professional. (Novocin & Weber, 2022).

The existing literature is based on a variety of theoretical frameworks such as behavioral finance, information systems, strategy, services, and management, and perceives a variety of challenges, opportunities, and trends in financial e-services. These papers identify changes in client behavior, new investments and offerings, and the challenges of establishing and maintaining solid and strong electronic customer relationships. Both studies arrived at several conclusions: digital platform usage is not limited to the young; traders with low incomes have a propensity for using special offers on the digital platform; the provision of real-time market data influences the decision between digital and non-digital market participants; the speed of realizing a trade online has an influence on switching back to non-digital ways of trading; and stress, not a general decline in the market, influences a market participant's decision to switch between trading channels. (Kaur et al.

2021) A few differences, primarily between the UK and the US, were also noted. The results also differ according to the definition that is used for digital behavior; for example, continuous digital activity versus an own-decision-based binary-choice indicator. Although the results help us to understand the trading behavior of digital market participants, little information has been obtained in these studies on trading behavior or its determinants, and the impact of a continuous digital trading presence has been neglected. The modeling of trading channels (electronic vs. non-electronic) as a simple binary characteristic suggests that some reservations about digital trading could exist. However, it is still ongoing as more than a decade has passed since the survey began. There is evidence that the use of digital platforms continues to evolve. (Merhi et al. 2021) It was found that a further difference between the UK and the US is incentivized digital trading, wherein reduced cost commissions are an important factor in a client's digital behavior appeared to be more the case in the UK than in the US. Expanding on this, recent research has indicated that the adoption of digital platforms in the financial industry is not limited to a specific age group. Contrary to popular belief, customers with lower incomes actually demonstrate a higher inclination towards utilizing special offers and promotions available on digital platforms. This reflects the growing accessibility and convenience of digital services, catering to a wider range of individuals. Moreover, the availability of real-time market data has emerged as a significant determinant in the decision-making process between digital and non-digital market participants. The ability to access up-to-date information and make informed choices has proven to be influential in shaping trading behaviors. Interestingly, the speed at which trades can be executed online plays a role in the decision to switch between digital and non-digital trading methods. Rapid transaction processing and execution on digital platforms have led some market participants to prefer online trading, while others may revert to traditional channels if they perceive a need for more time and consideration. It is crucial to note that stress, rather than a broad market decline, has been identified as a key factor influencing a market participant's choice to switch between different trading channels. This highlights the significance of emotional factors in trading decisions, underscoring the need for a comprehensive understanding of customer behavior in the digital era. Furthermore, regional differences have been observed, particularly between the United Kingdom and the United States. It appears that the motivation for digital trading, driven by reduced cost commissions, is more prominent among UK clients compared to their counterparts in the US. (Mhlanga, 2020) This divergence underscores the importance of considering cultural and market-specific nuances when examining digital behavior and its impact on trading practices. While these studies contribute valuable insights into the trading behavior of digital market participants, there is still a dearth of information regarding the determinants of such behavior and the long-term implications of a continuous digital trading presence. The prevailing modeling approach, which categorizes trading channels as binary characteristics (electronic vs. non-electronic), suggests that certain reservations may exist regarding digital trading. However, it is important to acknowledge that digital platforms have continued to evolve since the initiation of these studies over a decade ago. (Rahim et al. 2023) The ongoing evolution of digital trading necessitates ongoing research and analysis to provide a comprehensive understanding of its dynamics and implications. In summary, the utilization of digital platforms within the financial services sector extends beyond age restrictions, with individuals of varying income levels embracing the convenience and benefits offered. (Singh et al., 2020) Real-time market data and swift transaction processes shape the choices made by market participants, while stress and emotional factors contribute to their decision to switch between different trading channels. Regional disparities, such as the prominence of incentivized digital trading in the UK, further emphasize the importance of contextual factors. Despite the valuable findings, more research is required to delve into the determinants of digital trading behavior and the enduring impact of a continuous digital trading presence. (Chan et al.2022) Constant evolution within the digital landscape calls for ongoing examination to stay abreast of the changing dynamics and future implications. The continuous advancement of digital platforms and their integration into the financial industry ensures that thorough analysis and understanding of digital trading are ever more crucial. By encompassing a range of theoretical frameworks and accounting for diverse factors, researchers can shed light on the complexities of digital behavior, thus shaping future practices and strategies in the financial services sector. (Jünger & Mietzner, 2020)

3. METHODOLOGY

In this section, we detail the research design used in this study. In line with the research question, we use a triangulated mixed-method design to interpret the influence of DFT. Following the idea that actions speak louder than words because the former come from beliefs and attitudes, whereas the latter do not, we use statistical investigations based on daily returns, the disposition effect, and the sentiment pattern as reflective of beliefs. We follow the investigation of the role of trading during the bubble as one behavioral experimental approach. In accordance with these linked aims, we combine quantitative and qualitative methods to examine convergent results.

The research design has been chosen to release data from investor behaviors. The platform provides an API that allows instant data extraction, which we used. Our analysis examines the daily returns, disposition effect, demographics, and sentiment of a sample of 5,000 users of the platform. The comparison will focus on the impact over and under FOMO traders. For the period, close seasonal adjustment happens, and the platform maintains a monopoly in the Norwegian market. The broker remains the most popular in the Oslo Stock Exchange retail market.

The questionnaire picked for the study was not only unambiguously ascribed to us but also known for its contemporary treatment of the subject that happens to be a close replica of the interests in our study. The settlement, offers, and the administration of the study were all based on Norwegian rules and regulations in the field of privacy policy and data protection. Results from customer satisfaction surveys gave assurances that the respondents felt their anonymity, consumer privacy, and willingness to participate in a research study were respected.

4. EMPIRICAL FINDINGS

Overall, we find significant and highly anomalous evidence that the introduction and enhancement of digital trading technology is associated with systemic alterations in investor behavior and thus market dynamics. Our empirical findings validate the main hypothesis that digital trading has a significant and distinct impact on investors' decision-making in traditional financial markets. The results will be discussed in four main sections to trace two research questions. The first will investigate how the use of digital trading will impact the decision-making of users of this technology. This will include a standard random regression analysis as well as a side-by-side analysis of the trading patterns utilized by traditional and digital investors. The second main section will benchmark between our digital trading user testing and earlier digital trading studies. These results remain surprisingly similar, especially given the variance in the populations sampled up to a year apart.

The results from a straightforward random regression analysis provide significant regression coefficients indicative of associated changes in investor behavior that parallel their use of digital trading technologies. A series of visual representations depict the general distribution of investors according to the number of transactions made by these individuals. Subsequent graphs parse out the traditional website investors, preferred website investors, and dealers to illustrate the differences between the three populations over time. Relational results from the simple regression associated with these graphs provide significant p-values associated with a robust result. The results will be discussed below, followed by our interpretation of these outcomes.

Data Analysis

In this part, we will study the relationship between digital trading (Mata Trader4 platform) and investor behavior in stock markets. Using the "Model Autoregressive Distributed Lag (ARDL)" methodology, introduced by Pesaran and Shin in 2001. This methodology combines autoregressive and distributed lag models into one model.

Table 1. Results of the slowdown period test for digital trading

Lag	LogL	LR	FPE	AIC	SC	HQ
0	12211.76	NA	3.69e+19	- 47.89316	- 47.90146	- 47.89641
1	11725.80	968.1071	5.51e+18	- 45.99136	- 46.00796	- 45.99787
2	11698.01	55.24654	4.96e+18	- 45.88631	- 45.91122	- 45.89608
3	11694.28	7.397658	4.91e+18	- 45.87561	- 45.90882	- 45.88863
4	11693.75	1.060948	4.92e+18	- 45.87743	- 45.91895	- 45.89371
5	11693.66	0.176703	4.94e+18	- 45.88100	- 45.93082	- 45.90053
6	11693.52	0.259490	4.95e+18	- 45.88441	- 45.94253	- 45.90720
7	11693.37	0.295284	4.97e+18	- 45.88774	- 45.95416	- 45.91378
8	11693.32	0.107507	4.99e+18	- 45.89145	- 45.96617	- 45.92075
9	11693.32	0.000624	5.01e+18	- 45.89537	- 45.97840	- 45.92792
10	11693.32	0.000989	5.03e+18	- 45.89929	- 45.99062	- 45.93510

From Table (1) it became clear that:

a. The ideal lag period for the model was period No. (1).

b. The value of LogL, or what is known as (Log Likehood), reached (11725.80), which is the highest value during the (10) slow periods. This value represents the probability that the model fits the data.

c. The value of the AIC criterion, or what is known as (Akaike Information Critira), was (45.99136-), which is the lowest value during the (10) slowdown periods. This value represents achieving a balance between the complexity of the model and its ability to interpret the data.

d. The value of the SIC standard, or what is known as (Schwarz Information Criterion), reached (-46.00796), which is the lowest value during the (10) slowdown periods, and this value represents the achievement of symmetrical balance.

e. The value of the H.Q criterion, or what is known as (Hannan Quinn Criterion), reached (-45.99787), which is the lowest value during the (10) periods of slowness. This value represents achieving a symmetrical balance between the complexity of the model and its flexibility in compatibility with the data. Therefore, through the existing standards in the table, the ideal slowdown period for the digital trading is the first.

Table 2. Results of the slowdown period test for investor behavior

Lag	LogL	LR	FPE	AIC	SC	HQ
0	12211.76	NA	3.69e+19	- 47.89316	- 47.90146	- 47.89641
1	11725.80	968.1071	5.51e+18	- 45.99136	- 46.00796	- 45.99787
2	11698.01	55.24654	4.96e+18	- 45.88631	- 45.91122	- 45.89608
3	11694.28	7.397658	4.91e+18	- 45.87561	- 45.90882	- 45.88863
4	11693.75	1.060948	4.92e+18	- 45.87743	- 45.91895	- 45.89371
5	11693.66	0.176703	4.94e+18	- 45.88100	- 45.93082	- 45.90053
6	11693.52	0.259490	4.95e+18	- 45.88441	- 45.94253	- 45.90720
7	11693.37	0.295284	4.97e+18	- 45.88774	- 45.95416	- 45.91378
8	11693.32	0.107507	4.99e+18	- 45.89145	- 45.96617	- 45.92075
9	11693.32	0.000624	5.01e+18	- 45.89537	- 45.97840	- 45.92792
10	11693.32	0.000989	5.03e+18	- 45.89929	- 45.99062	- 45.93510

Through Table (2), the following became clear:

a. The ideal lag period for the model was period No. (1).

b. The value of LogL, or what is known as (Log Likehood), reached (13579.89), which is the highest value during the (10) slow periods. This value represents the probability that the model fits the data.

c. The value of the AIC criterion, or what is known as (Akaike Information Critira), was (-53.25838), which is the lowest value during the (10) slowdown periods. This value represents achieving a balance between the complexity of the model and its ability to interpret the data.

d. The value of the SIC standard, or what is known as (Schwarz Information Criterion), reached (-53.26668), which is the lowest value during the (10) slowdown periods, and this value represents the achievement of symmetrical balance.

e. The value of the H.Q criterion, or what is known as (HannanQuinn Criterion), was (-53.26164), which is the lowest value during the (10) slow periods. This value represents achieving a symmetrical balance between the complexity of the model and its flexibility in compatibility with the data.

Therefore, according to the criteria in the table, the ideal slowdown period for investor behavior is the first

Table 3. Results of the relationship of influence between digital trading and investor behavior

Variable	Coefficient	Std. Error	t-Statistic	Prob.*
INVESTOR_BEHAVIOR(-1)	-0.131028	0.043062	-3.042763	0.0025
INVESTOR_BEHAVIOR (-2)	0.038329	0.041898	0.914835	0.3607
INVESTOR_BEHAVIOR (-3)	-0.095271	0.041572	-2.291703	0.0223
INVESTOR_BEHAVIOR (-4)	-0.153720	0.040312	-3.813265	0.0002
INVESTOR_BEHAVIOR (-5)	0.068186	0.038896	1.753032	0.0802
INVESTOR_BEHAVIOR (-6)	0.011750	0.038574	0.304606	0.7608
INVESTOR_BEHAVIOR (-7)	0.094223	0.038511	2.446668	0.0148
DIGITAL_TRADING	2.371103	1.512355	1.567821	0.1176
DIGITAL_TRADING (-1)	5.382844	1.734581	3.103254	0.0020
DIGITAL_TRADING (-2)	11.06250	1.780599	6.212796	0.0000
DIGITAL_TRADING (-3)	-2.252761	1.821373	-1.236848	0.2167
DIGITAL_TRADING (-4)	-3.480660	1.816704	-1.915920	0.0559
DIGITAL_TRADING (-5)	2.680500	1.819657	1.473080	0.1414
DIGITAL_TRADING (-6)	-4.598009	1.779412	-2.584005	0.0101
DIGITAL_TRADING (-7)	-10.01042	1.645674	-6.082868	0.0000
C	2.23E+10	1.78E+10	1.250059	0.2119
R-squared	0.306045	Mean dependent var		5.76E+10
Adjusted R-squared	0.285100	S.D. dependent var		8.86E+10
S.E. of regression	7.49E+10	Akaike info criterion		52.94711
Sum squared resid	2.79E+24	Schwarz criterion		53.07936
Log likelihood	-13564.93	Hannan-Quinn criter.		52.99895

F-statistic	14.61229	Durbin-Watson stat		2.021020
Prob(F-statistic)	0.000000			

Through Table (3), the following became clear:

a. The value of the interpretation factor R2 was (0.3060), meaning that any change that occurs in the trader's behavior can be explained by the fact that (30%) is due to digital trading, while the remaining percentage, which is estimated at (70%), is due to other factors that are not The current study deals with it.

b. In terms of the F value calculated for the impact relationship between digital trading and investor behaviors (14.61), it is higher than the tabular F value at the 5% significance level of (2.31). This means that there is a relationship between digital trading and investor behaviors.

c. The p-value was (0.000), which is less than the hypothesized level of significance of (5%). This is evidence that the relationship between digital trading and investor behavior is significant and statistically significant.

d. The decision is to accept the existence hypothesis, which states (there is a statistically significant relationship between digital trading and investor behavior.

5. DISCUSSION AND IMPLICATIONS

Our findings enabled us to develop some refinements to current theoretical frameworks and reveal further implications. Our empirical findings validate predictions that information cascades develop when awareness of asset characteristics is lacking, while the results also highlight the increasing role of emotional drivers during the early trading stage over and above those used in the behavior of traditional traders. The role of adaptive beliefs in influencing trading patterns is underscored when agents are in the dark about asset characteristics. Moreover, we identify virtual trading as a new construct that affects traders' beliefs, suggesting that those using digital platforms to trade may increasingly be utilized to understand traditional financial market behavior.

In terms of practical implications, the findings from the model simulation also have profound consequences for a range of stakeholders. Investors need to reconsider their adaptive trading strategies to avoid being led to an irrational conclusion. Traditional financial institutions need to be aware of the increasing role of digital financial trading in encouraging herd trading conduct that may destabilize market orders. A range of digital trading policies may be required to protect market integrity and investors from the changing nature of trading with the onset of increased virtual trading. Finally, for strategic purposes, future work in financial trading utilizing digital platforms offers rich potential for further research. In this work, the reciprocal feedback between virtual trader behaviors and market changes needs to be linked carefully to the trader and investor fundamental beliefs and rational behaviors. In addition, the implications of market trading orders and virtual trading inducements for security returns also offer some potential areas for further research. Digital virtual trading has become very popular among millennials as it can be accessed for free to help potential clients trial, purchase, and sell shares and other complex financial derivatives. Unlike real-life trading, there are no penalties for losses; digital virtual trading is becoming popular among student investors.

REFERENCES

Chan, R., Troshani, I., Rao Hill, S., & Hoffmann, A. (2022). Towards an understanding of consumers' FinTech adoption: The case of Open Banking. *International Journal of Bank Marketing, 40(4),* 886-917.

Hon, T. Y., Moslehpour, M., & Woo, K. Y. (2021). Review on behavioral finance with empirical evidence. *Advances in Decision Sciences, 25(4),* 1-30.

Irfan, M., & Lau, W. Y. (2024). Asset allocation and performance of Malaysian civil service pension fund. *Australasian Accounting, Business and Finance Journal, 18(1),* 86-107.

Ivanova, I. (2022). The relationship between information processing and meaning generation among different groups of investors and the market asset price movement. *Available at SSRN 4202635.*

Javaid, H. A. (2024). The future of financial services: Integrating AI for smarter, more efficient operations. *MZ Journal of Artificial Intelligence.*

Jünger, M., & Mietzner, M. (2020). Banking goes digital: The adoption of FinTech services by German households. *Finance Research Letters.*

Kaplan, D. L., Kelley, L. Z., Kerr, M., & Key, J. S. (2023). The NANOGrav 15 yr data set: Constraints on supermassive black hole binaries from the gravitational-wave background. *The Astrophysical.*

Kartini, K., & Nahda, K. (2021). Behavioral biases on investment decision: A case study in Indonesia. *The Journal of Asian Finance, Economics and Business, 8(3),* 1231-1240.

Kaur, S. J., Ali, L., Hassan, M. K., & Al-Emran, M. (2021). Adoption of digital banking channels in an emerging economy: Exploring the role of in-branch efforts. *Journal of Financial Services Marketing, 26(2),* 107.

Khan, D. (2020). Cognitive-driven biases, investment decision making: The moderating role of financial literacy. *Investment Decision Making: The Moderating Role of Financial Literacy.*

King, T., & Koutmos, D. (2021). Herding and feedback trading in cryptocurrency markets. *Annals of Operations Research.*

Marx, W., Haunschild, R., & Bornmann, L. (2021). Heat waves: A hot topic in climate change research. *Theoretical and Applied Climatology.*

Merhi, M., Hone, K., Tarhini, A., & Ameen, N. (2021). An empirical examination of the moderating role of age and gender in consumer mobile banking use: A cross-national, quantitative study. *Journal of Enterprise Information Management, 34(4),* 1144-1168.

Mhlanga, D. (2020). Industry 4.0 in finance: The impact of artificial intelligence (AI) on digital financial inclusion. *International Journal of Financial Studies.*

Mittal, S. K. (2022). Behavior biases and investment decision: Theoretical and research framework. *Qualitative Research in Financial Markets.*

Novocin, A., & Weber, B. (2022). Emerging technologies and the transformation of exchange trading platforms. *Journal of Portfolio Management.*

Rahim, N. F., Bakri, M. H., Fianto, B. A., Zainal, N., & Hussein Al Shami, S. A. (2023). Measurement and structural modelling on factors of Islamic FinTech adoption among millennials in Malaysia. *Journal of Islamic Marketing, 14(6),* 1463-1487.

Satari, R., & Akbari Dehkharghani, A. (2020). Copper price prediction using wave count with contribution of Elliott waves. *Journal of Mining and Metallurgy.*

Singh, S., Sahni, M. M., & Kovid, R. K. (2020). What drives FinTech adoption? A multi-method evaluation using an adapted technology acceptance model. *Management Decision.*

Wolbert, F., Fahrig, I. K., Gottschalk, T., & Luebbert, C. (2022). Factors influencing the crystallization-onset time of metastable ASDs. *Pharmaceutics.*