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Research paper

Unraveling the impact of Iranian currency exchange on central bank digital currency: navigating through history-oriented bias

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Abstract:
This study examines the dynamics of the Iranian foreign exchange market and its impact on the exchange rate used by traders, and not the official rate in Iran. The study aims to extend Fama's theory of market efficiency and proposes a new model to define the opposite point called "Historical bias". The study applied the ARIMA and Markov switching models and dynamic conditional correlation to measure the speed of information circulation and to investigate the origin of the Iranian foreign exchange market's impact on the trader rate of the Dollar market. The study analyzed the convergence of the Iranian foreign exchange market based on different rates, the exchange rate used by traders, and the official rate and its effect on developing CBDC in Iran. The results of this study show that based on Fama's theory of market efficiency the foreign exchange market in Iran could have a 15% history-oriented bias, which is significant and would be an important problem for the launching of CBDC in Iran.

Keywords: Central bank digital currency (CBDC), Market efficiency, Dynamic conditional correlation (DCC), Iran currency exchange, History-oriented bias.
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1 Introduction

Unlike traditional bank reserves or clearing account balances, the Central Bank Digital Currency (CBDC) is a digital currency. Many countries are interested in CBDC given the age of digital technology. Central banks in many countries that are experimenting with, piloting, and implementing CBDC have embraced it. Despite the capability impact of CBDC on deposits of bank and its impact on various other bank activities, banks are obliged to consider it in their banking operations [50]. Globally, many central banks have explored the possibility of introducing CBDC into their economies in recent years. The United States, England, Singapore, Brazil, European Union countries, India, Thailand, Venezuela, and several other countries are actively considering the introduction of CBDC in their monetary systems.

The overview of a central bank digital currency has rarely been studied to determine whether it affects bank performance. For example, according to Chiu et al. (2019), a CBDC with a reasonable interest rate will encourage banks with market power to increase their interest rates on consumer deposits, thereby attracting extra deposits into banks and allowing banks to lend further. Jun and Yeo (2021) analyze a CBDC for a macroeconomic account to find out how it affects a bank's credit supply and default risk. As findings show that demand deposits can be replaced with CBDCs since CBDCs help lower the cost of money, but they can also rise banks' default risk if term deposit rates do not increase.

Kim and Kwon (2022) conducted a research study utilizing a monetary general equilibrium model to examine the potential outcomes of central bank digital currency on the supply of bank loans. The authors show that introducing credits in CBDC accounts reduces bank credit availability, raises the nominal interest rate, lowers a bank's reserve-deposit ratio, and raises the chance of bank alarm when cash reserves are depleted. According to Andolfatto (2021), the implementation of a central bank digital currency does not harm bank lending. In fact, it might even encourage bank lending as competition increases, which would lead banks to increase interest rates on deposits interest in more funds. This, in turn, would raise bank liquidity and result in increased bank lending. According to García et al (2020), they agree with Andolfatto (2021) that banks can handle short-term impacts on their profits and liquidity caused by the implementation of CBDC, as long as the expenses of deposit money are short and the CBDC does not earn interest. Lastly, according to Juks (2020), the implementation of central bank digital currency may theoretically reduce the availability of bank loans. However, central banks possess the necessary tools to counteract any negative impact on the loaning capability of banks when intervention is required. Ozili, Peterson K (2023) presented that the event that CBDC-encouraged bank intermediation causes a decrease in bank deposits and lending, banks may turn to accruals like loan loss provisions to regulate their earnings and report them accordingly. Equally, it has been reasoned that CBDC has been positively received by users by many scholars ([47]). In a

study published by Chien et al (2023), a positive correlation has been observed between the variability in currencies of central banks and the implied volatility of firms. Additionally, a firm's implied volatility can be reduced when its conditions are healthier. Furthermore, Central bank digital currency still exhibits a positive correlation with implied volatility for investment grade, speculative grade, and unrated firms.

Davoodalhosseini (2022) shows that CBDC can be used to allocate funds strong effectively than cash if the costs of with CBDC are low. Furthermore, introducing a CBDC in certain countries, like the U.S. and Canada, can increase consumption. Keister, O., and Monnet, C (2022) research was conducted to assess whether the Implementing a Central Bank Digital Currency (CBDC) would have an impact banking system strength. CBDC reduces banks' exposure to runs by reducing maturity transformation, which increases maturity transformation. Additionally, policymakers can identify weak banks and resolve them sooner by monitoring the flow of funds into CBDCs, which decreases depositors' incentive to run from them. Keister, T, and Sanches, D., (2019) stated Digital currencies have the advantage of promoting effectiveness in exchange, but they can also discourage bank deposits, increase banks' funding costs, and reduce investment. However, central banks are often able to raise welfare through the introduction of digital currencies.

According to research conducted by Castrén et al (2022), CBDC may lead to a shortage of funding for banks, which might spread to alternative industries. Moreover, there have been significant adjustments to all sectors' balance sheets move securities prices dramatically and affect the structure of financial networks. In the results of Tong and Jiayou (2021), it is demonstrated that DC/EP has a limited substitution effect on bank deposits. However, the unit impact of DC/EP can enhance economic growth by 0.15 percent. As well as having a positive economic effect, it also reduces leverage to a certain degree, which reduces systemic financial risks. A recent study by Wang, G., and Hausken, K., (2022) shows that the central bank selects a further in times of increasing household consumption output elasticity, household field output elasticity decreases, leading to a negative interest rate, there is an increase in both CBDC and non-CBDC operation efficiency, a decline in household consumption transaction efficiency, a rise in household transaction cost scaling, a decrease in the central bank's profit per household scaling parameter, a decrease in household monetary energy, and a decrease in non-CBDC interest rates. According to Allen et al. (2020), CBDC presents a wide scope of new opportunities, however, it similarly comes with several tasks. Performance, privacy, and security are the major technical challenges faced by CBDC designers. In addition to efficacy, a larger tax base, flexible monetary policy, payment of backstop, and financial inclusion, they summarize the major advantages of CBDC, namely efficiency, a broader tax base, and greater financial inclusion.

In addition to reviewing the literature, Carapella and Flemming (2020) evaluate the effect CBDCs have on commercial banks, financial stability, and monetary

policy. Oh and Zhang (2020) examine a CBDC utilizing a binary-sector monetary model with official and unofficial economies. The authors demonstrate that tax fall and a positive CBDC interest rate are beneficial for increasing CBDC acceptance and enhancing its efficacy. According to George et al. (2020), CBDCs with adjustable interest rates have macroeconomic implications. Their analysis is extended to the context of foreign capital flows in an open economy. CBDCs with adjustable interest rates increase welfare, and quantity rules deliver the best welfare outcomes. The study by Bindseil and Fabio (2020), the CBDC should be remunerated on a two-tier system in order to reduce intermediation between banks, and negative interest rate policies and maintain financial stability, Four key objectives could be achieved by tiered CBDC remuneration, namely: providing marvelous CBDC as earnings of payment to households, allowing CBDC to be offered in a quantitatively unimpeded fashion to anyone, minimizing organizational or recurring a intermediation risks, and allowing negative interest rates for existing customers. A CBDC will achieve the same allocations as a private financial intermediation firm without a banking panic (Villaverde, 2020). Their rigidity, however, shows that when panic strikes, the central bank's contracts with investment banks can deter scores. As a result, the central bank has a higher level of stability than the sector of commercial banking. Eventually, in this case, the central bank has a monopoly over deposits, which the depositors assume ex ante, removing them from commercial banks. The maturity transformation might be endangered by this monopoly. Farajnezhad, M et al (2020), show that the interest impact of monetary transfer mechanism at the Gini coefficient as an indifference index in OECD countries is positive and insignificant (probability is 0.18) with a coefficient of 0.004 and it shows that raising interest rates will increase the inequality in these countries. Additionally, the effect of the capital market on the inequality is also positive with a coefficient of 0.001 and a significant probability of 0.002. It shows the positive effect of bank deposits on income inequality. According to Ronaghi (2022), the findings demonstrate there is a direct correlation between the terms of sanctions, usage, and facilitating conditions and users' perceived value of digital currencies for their use as a medium of exchange; as a consequence of these findings, in a country that is subject to sanctions, such as Iran, the usage of digital currencies is becoming more acceptable as a means of circumventing economic sanctions and, as a result, of making commercial payments.

Since the introduction of market efficiency theory by Fama in 1970, with its gist of the rapid speed of information circulation and the immediate effect of information on prices, many studies have been conducted in this field. Although the speed of information circulation is a necessary condition for the health of a market, only examining the speed of information circulation without considering the goals of forming a market or index, especially indices for controlling and guiding another market, cannot be beneficial. Therefore, in this work, besides the theoretical expansion of the market efficiency theory, we provide a model for measuring both the

speed of information circulation and the effectiveness of the controller's indicators. For this purpose, we used the ARIMA model and Markov switching model to measure the rapid flow of information more accurately and to measure the outcome of two indices or two markets on each other; we used conditional correlation on the corresponding days and a one-day lag back and forth. For this purpose, the research of Tajdini et al. (2022) divides behavioral finance into binary categories of previous-oriented bias and recent-oriented bias. In this study, the opposite point of the definition of market efficiency called history-oriented (or past-oriented) bias, was examined in two markets, including the exchange rate used by traders, and the official rate, in the period from June 20 to October 30, 2022.

In Iran, the existence of dual exchange rates, where traders use a different rate than the official one, can pose challenges for businesses and the potential launch of a Central Bank Digital Currency (CBDC) in the following ways:

- Business Operations
  Businesses often face uncertainties due to the discrepancy between the trader-used rate and the official rate. This duality can complicate financial planning, pricing strategies, and international transactions, impacting the overall stability of operations.

- Economic Distortions
  Dual exchange rates can contribute to economic distortions, affecting pricing mechanisms and creating arbitrage opportunities. This may lead to market inefficiencies, hindering the smooth functioning of the economy.

- CBDC Implementation
  Launching a CBDC requires a stable and transparent economic environment. The existence of dual exchange rates may raise concerns about the effectiveness of monetary policies, potentially impacting the successful implementation and acceptance of a CBDC.

- Foreign Exchange Reserves
  The presence of dual rates may complicate the management of foreign exchange reserves. Central banks typically rely on accurate exchange rate data for effective policy decisions, and the existence of multiple rates can hinder these efforts.

So, the dual exchange rate system in Iran introduces complexities for businesses, creates economic distortions, and could pose challenges for the successful launch and adoption of a CBDC in the future.

1.1 Market efficiency

The efficient market hypothesis, created via the contributions of important papers such as [22], [45], and Malkiel & Fama (1970), was the major asset pricing the-

ory in the early mid-1960s. The efficient market hypothesis suggested by Malkiel (1962) and Fama (1965) argues that the value of an asset should instantly consider essential data about the asset [22]; [46]. However, efficient market hypotheses are established in part on unverifiable expectations and models. Yet, it is possible to examine the main statements of efficiency separately using well-known tests such as the variance ratio and the analysis recommended using researchers [40]; [58].
Based on neoclassical economics, the efficient market hypothesis assumes perfect competition. Perfectly, a market with perfectly competitive behavior is characterized by rational behavior and a willingness to take risks to maximize profits. This assumption about the behavior of market members also applies to the efficient market hypothesis presented by Fama (1965) and Malkiel (1962). This emphasizes the need to estimate hypotheses that influence market participants' behavior under uncertainty before testing efficient market hypotheses (Fama, 1995; Malkiel, 1962).
Before beginning to test an efficient market hypothesis, we need to describe facts in the background of this study. As proposed by Malkiel & Fama (1970) and Malkiel (2003), all available data should be showed in prices allowing to the efficient market hypothesis ([40]; [45]). It is common to recognize the difference between elementary and non-elementary info ([8]). Thus, the data is the total of:

- Cochrane (1991) and Malkiel (2003) proposed basics such as government bond market yields and macroeconomic variables.

- Caballero and Krishnamurthy (2008) proposed the inclusion of non-basic data, such as news information, which may not be directly related to assets but can significantly impact prices. Examples of such events include 9/11 terrorist attacks, Lehman Brothers' bankruptcy in 2008, and the earthquake in Japan.

- As a result of rational, profit-maximizing behavior among market participants and a consistent, complete reflection of evidence in prices, an efficient market has been determined [45]. The main impact of efficient market hypotheses is that information selection is faster and is immediately reflected in asset valuations [45]. This shows that there aren't any possibilities for arbitrage that allow for enormous rewards lacking excessive risk [45]. In an efficient market, competition means there is no opportunity for extreme risk-adjusted returns [46]. However, it is incorrect to say that according to the efficient market hypothesis, market prices are always right, and all market participants continuously behave rationally and profitably.

As investigated in various outcomes during the current financial and sovereign debt crises, the main crisis with price information is that no one can forecast the effect of the data, especially in uncertain times. Therefore, the equilibrium price cannot be verified accurately in uncertain times ([22]). Moreover, the immediate adjustment property of the efficient market hypothesis proposed by Fama (1965) implies that prices follow a random walk model, which can lead to continuous and independent

price changes ([43]).
In the long run, market price movements are partly predictable ([44]). This builds the efficient market hypothesis very challenging to predicted prices and profits [62]. The main reason behind this is that if prices and profits are predictable, this implies the existence of infinite profits and economic instability.
Following the financial crisis, many organizing, financial markets, and academia criticized the efficient market concept [5]. Their logic is based on a critical statement that supports the efficient market hypothesis, which states that market prices would represent all existing data. The presented authorities and market some players may have had a mistaken belief that market prices were accurate, given the information available to them resulting in asset price bubbles. Like other sound theories, the efficient market hypothesis possesses significant restrictions [5]. However, the post-global financial crisis critique appears to be inflated. Since Fama (1965) developed the theory of the efficient markets hypothesis, this argument is incorrect because there were numerous crises based on asset price bubbles before the birth of the efficient markets hypothesis [22]. According to the efficient market hypothesis, current asset values are correct based on all available information [5]. This requires market players to accept asset values as accurate. But, before the financial crisis, several market members felt that asset values were "wrong" and might outperform the market. This seems to indicate that the price is correct for all informed markets. Nevertheless, this is false because the efficient market hypothesis does not state that prices are precise/accurate. It simply states that prices should reflect all accessible data [44]. Moreover, these deviations can become severe over time [7]. Not all information is accessible to market participants [29].
The efficient market hypothesis relies heavily on the critical assumption that asset prices are brought back to their fundamental values by rational arbitrage traders who possess ample information and financial resources. The reality of these arbitrageurs has little impact on the activities of other market players, and prices can deviate from fundamentals. [2]; [29]
Another important argument is that markets often repeat sentences when efficient market hypotheses are insufficient to explain anomalies [2]; [28]. Therefore, it is necessary to study the psychology of market participants ([14]; [37]). As a result, behavioral finance theory is applied.
The study conducted by Fakhry and Richter (2015) investigates the impact of the current financial and sovereign debt crises on the sovereign debt markets of the United States and Germany and find that both markets are generally unstable and inefficient ([21]). The US dataset suggests markets are efficient, but the sub-sample suggests mixed results, suggesting that both crises are impacting market efficiency in the US and Germany. On the contrary, Fakry et al. (2016) expanded the methods employed in Fakhry & Richter (2015) to the gypsum market and found mixed evidence of efficiency in times of crisis. This raises the possibility of using behavioral finance theory to describe the efficiency of the US dataset ([21]). Since market

participants over and under-reacted to information at various points in time, one probable conclusion is that the over- and under-reactions cancel each other out, resulting in a consistent perception of market efficiency.
As per the Efficient Markets Hypothesis, the generation of excess profits is not feasible through technical or fundamental research as stock prices promptly reflect any new market information. As per the efficient market hypothesis, stock prices rapidly incorporate any newly available information in the market. Both technical analysis, which involves examining past stock prices to predict future prices, and fundamental analysis, which involves analyzing financial data, have the potential to enable investors to outperform a portfolio of equities chosen randomly.
So far, there have been many definitions of an efficient market. However, the authors contend that every definition has a mistake that must be fixed. One factor, the target, is not considered in any definition of an efficient market, which is described as one that responds to news and information. According to the definition of the authors of this article, an efficient market is one that reacts to news and information and achieves its goal according to that news.

1.2 Behavioral Finance

Behavioral finance refers to investor psychology and application to financial decision making. We realize people have reactions that affect their decisions. There is a great danger of stock market disaster as a result of such inefficient and irrational decisions. Mackay (2003) documents perhaps the most historical incidence of such a disaster. He reports three events: the Tulip Bubble of the 1630s, the South Sea Society Bubble of 17111720, and the Mississippi Society Bubble of 17191720. Of these, the Tulip Bubble, commonly known as Tulipomania, is perhaps the most excellent cited story. The first introduction of the exotic flower "tulip" to the Dutch stock market dates back to the Dutch Golden Age. The culture and buying of tulips began on a large scale. Shortly, a tulip boom spread across Holland, and people even began to invest in tulip stocks. The value of this flower naturally increased, and the bulbs sold for more than ten times a skilled craftsman's annual salary during their heyday. The Dutch stock market eventually collapsed as investors felt they had spent too much on commodities of little waste, like tulip flowers. This realization caused tulip prices to plummet, resulting in heavy losses. Results like Tulipomania threaten the sanity of investors. In the ideal situation where this method can be applied, the market is information efficient. But most markets are useless. The existence of market anomalies, such as speculative bubbles, over-reactions and under responses to new data, is evidence that there is more to the financial decision-making process than cold, calculating, and rational agents. Consequently, the need to understand such anomalies and the accompanying flaws in human reasoning has pioneered behavioral finance [41]. Recent studies have focused on a field of study called "behavioral finance" looks at how psychology affects how financial professionals behave and how it affects the stock market [60]. This demonstrates the character

of psychological bias and its detailed behavioral consequences in decision making. Studies conducted by behavioral specialists (Curt Hunter et al., 2002) have revealed that psychological biases, such as overconfidence, self-attribution bias ([13]), and herding behavior ([58]), are significant factors that contribute to these anomalies. This makes behavioral finance a highly relevant topic today.

Traditional financial theory was well constructed for making calculated financial decisions. Conversely, they were incapable of describing the stock market's volatility. These disorders or anomalies sometimes manifest themselves in the form of stock market bubbles, market over- or under returns, momentum, and exchanges. It is in this pattern that behavioral finance began to develop, seeking to provide a behavioral explanation for such anomalies. Pioneering research in behavioral finance came from psychologists [34]Kahneman. The concept of prospect theory was proposed (1979) In order to create the basis for behavioral finance, we need to analyze decision-making under risk. Prospecting theory's value function replaces the anticipated utility theory's utility function. This function assesses the "value" an individual puts on winning or losing. This feature explains why some wins and losses feel stronger than others. When there is a loss, it can be more painful than the happiness that comes from the gain. This is called loss aversion because losses are greater than gains. Therefore, there are three primary claims of prospect theory. A second follower suggests that people use reference points to assess a prospect's value. In general, their wealth level serves as this reference point, which determines wins and losses with potential clients. A third proponent claims that losses are greater than gains. The need to avoid losses is much greater than the urge to win, which is an individual tendency. Considered key research in behavioral finance, prospect theory forms the basis for biases such as loss aversion, framing, and disposal effects.

Various studies challenged the efficient market theory in the 1990s and 2000s [58]; [59]. Shleifer has created a behavioral model that covers an extensive series of market anomalies, counting the out performance of value companies, the dilemma of closed-end funds, the strong returns of stocks featured in market indexes, and the durability of stock bubbles. Shiller (1981, 2002) presents other discrepancies about EMH. In 1981, the authors showed that stock prices are far more volatile than current monetary theory can explain. Schiller emphasizes psychological and cultural variables in stock market bubble creation, as well as their effect on investor views. In another study, Jegadeesh and Titman also provided significant evidence for locomotion (Jegadeesh & Titman, 1993). The researchers found that individual stock prices tended to predict future prices on the same path. This result abuses even weaker forms of market efficiency.

2 Methodology

The dual exchange rate system in Iran (the exchange rate used by traders, and not the official rate) introduces complexities for businesses, creates economic distortions, and could pose challenges to the successful launch and adoption of a CBDC in the future. Launching a CBDC requires a stable and transparent economic environment. The existence of dual exchange rates may raise concerns about the effectiveness of monetary policies, potentially impacting the successful implementation and acceptance of a CBDC. The study aims to extend Fama's theory of market efficiency and proposes a new model to define the opposite point called "Historical bias". The study applied the ARIMA and Markov switching models and dynamic conditional correlation to measure the speed of information circulation and to investigate the origin of the Iranian foreign exchange market's impact on the trader rate of the exchange market, particularly the dollar market. In this section, after reviewing the ARCH models, as well as Conditional Covariance (CCC and DCC), there is an innovative formula based on this study (formula no: 11).

2.1 Dynamic conditional correlation

The time-dependent covariance matrix of return on assets must be estimated and predicted for several financial applications, involving risk management, asset allocation, and systemic risk assessment. Engle's GARCH-DCC technique has founded itself as one of the major paradigms in literature because of its flexibility and predictability (R. Engle & Sheppard, 2001). Briefly, the conditional variance matrix and the conditional correlation matrix are formed independently in the GARCH-DCC technique (R. Engle, 2002; R. Engle & Sheppard, 2001). The GARCH model is used to represent the conditional variance, while the dynamic conditional correlation (DCC) model is used to model the conditional correlation matrix [15]; [66]. Zhang (2006) applied to move usual models, exponential shifting averages, random walks, and several GARCH models to forecast the Shanghai and Shenzhen indices of the China Stock Exchange. The author realized that there is no single model that performs best in all conditions. For instance, asymmetric models such as GJRGARCH and EGARCH outperformed other GARCH models on the Shenzhen index but failed on conditional risk prediction of the Shanghai index. Abdelaal (2011) studied Egyptian stock exchanges from 1998 to 2009 and achieved that the EGARCH model was better at predicting volatility than others. Using the S&P index as an example, Liu et al. (2010) analyzed GARCH, EGARCH, ARCH, and GJR-GARCH models, finding that asymmetric models such as GJR-GARCH, EGARCH, and ARCH were much more helpful in predicting volatility than the type of error distribution. The Stockholm Stock Exchange daily returns are examined by Dritsaki (2107a), who found that asymmetric GARCH models are better predictors than GARCH-only models. The asymmetric EGARCH and PGARCH models were found to perform better in predicting future risk and return than the

symmetric GARCH models for the euro exchange rate against the Romanian currency by Cristina and Stelian (2017). Findings by Guo (2017a) on the Hong Kong Stock Exchange, Sarkar, and Banerjee (2006), Intaz et al. (2016) at the Dutch Stock Exchange, Dritsaki (2017) for the North and East Africa Stock Exchanges and Dritsaki (2017) for the Stockholm Stock Exchange price-to-earnings ratio on a daily basis can be used in asymmetric GARCH modes such as GJRGARCH and other models that consider leverage for risk forecasting outperformed the symmetric GARCH model for evaluation of the risk. An assessment of crude oil prices and exchange rates in 12 Asian countries was conducted by Hussain et al. (2017). As a result of their experiments, most Asian nations showed weak negative correlations between oil prices and exchange rates. Tsukuda et al. (2017) used a dynamic conditional compensation model to examine correlations between East Asian stock markets such as Japan, Singapore, and Hong Kong, and US stock markets. According to their findings, Singapore and Hong Kong markets exhibited significant correlations with global markets, particularly the US market, while Japanese markets had little influence on East Asian markets. According to Robiyanto (2018 a , b), there is a dynamic correlation between ASEAN-5 stock markets and global oil prices, as well as a dynamic integration of the Indonesian stock market with Asian and global markets.

During the previous two decades, researcher consider has focused on determining whether firms with superior ESG performance deliver higher financial returns to investors [28]; [30]. Conversely, instability in publicly reliable investing indexes has been seen and predicted in rare efforts (Sadorsky, 2014). Also, there has been no research that compares the conditional volatilities of SRI indexes to those of common indices. In existing research, dynamic conditional correlation (GARCH) (DCC-GARCH) models are highlighted as being ideal for examining volatility contagion in financial markets [60]. Engle (2002) verifies that the DCC model is a suitable method since it offers a realistic approximation of the linked process. Accordingly, Laurent et al. (2012) DCC analysis offered superior predictions when the most appropriate multivariate GARCH model was used. In addition, Sadorsky (2014) employed three multivariate GARCH models to evaluate the DJSI of socially responsible enterprises, gold price, and oil price, and discovered that the DCC model was best suited for the data on which correlations were to be determined. Mehrara et al. (2022) created a model of a past-oriented behavioral bias that is strongly connected to random walk theory. They developed a new model to measure the effects of past-oriented behavioral biases on some market indexes. According to the findings, the Cement Index has the biggest historical behavioral bias (57%), followed by the top 50 Index (46%), Chemicals (41%), and Petroleum Products (12%). The SandP index, on the other hand, exhibited no past-oriented behavioral bias. They claim that behavioral biases manifest themselves in two forms of acceleration theory: the continuation of the present trend in ARIMA models with positive coefficients and the opposite theory, in which the opposite of the current

trend has negative ARIMA coefficients. Tajdini et al (2022) and Mehrara et al (2022), divided behavioral finance into two general categories: past-oriented and current-oriented. Based on changes in P/E ratios, Tajdini et al. (2022) developed a model for measuring historical-oriented behavioral biases based on the random walk. According to the authors' study, policymakers should address the frictions and inefficiencies that persist in undeveloped financial markets, such as the Tehran Stock Exchange.

Based on ARCH models, an econometric instrument is examined to estimate and anticipate asset return volatility and turbulence using the conditional heterogeneity variance model. In this model, p represents the $2\sigma_{t-1}^2$ order or variance of the prior day, and q represents the power of ε_{t-1} or the disruptive factor of the earlier day.

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i} + \sum_{i=1}^{p} \beta_t \sigma_{t-i}^2 \tag{1}$$

This study can simulate the leverage effects provided by Black and French et al. (1976) utilizing the GJR-GARCH model. Asymmetry in the ARCH activity is similarly shown in the Glosten-Jagannathan-Runkle (993) GARCH (GJR-GARCH) model by Glosten, Jagannathan, and Runkle (1993). The GARCH process simulates the leverage effect. If $\varepsilon_{t-1} > 0$, then I=0 and if $\varepsilon_{t-1} < 0$, then $I = 1$ and leverage effects can be investigated with the assumption $\gamma > 0$.

$$\sigma_t = \omega + \sum_{i=1}^{p} (\alpha_i + \gamma_i I(\varepsilon_{t-1}))\varepsilon_{t-j} + \sum_{j=1}^{q} \beta_i \sigma_{t-j} \tag{2}$$

Nelson and Cao (1992) created the EGARCH model, which is a variation of the GARCH model that incorporates exponential characteristics. Officially, an EGARCH (p, q) : Asymmetry in the conditional variance is observed when the significance of $\gamma \neq 0$ is established. Leverage effects in this model may be investigated under the premise that $\gamma < 0$.

$$\log\log(\sigma_t^2) = \omega + \alpha_i |\frac{\varepsilon_{t-1}}{\sigma_{t-1}}| + \gamma(\frac{\varepsilon_{t-1}}{\sigma_{t-1}}) + \beta_1 \log\log(\sigma_{t-1}^2) \tag{3}$$

2.2 Conditional Covariance

Constant Conditional Correlation (CCC)

Originally, the Model of GARCH was used to calculate asset conditional variance. Divide the returns by their standard conditional variances to get the constant conditional correlation coefficient between assets.

$$p_i = \frac{q_{ij}}{\sqrt{q_{ii} q_{jj}}} \tag{4}$$

Dynamic Condition Correlation (DCC)

Originally, the GARCH model was used to calculate asset conditional variance. To determine dynamic conditional correlation coefficients between assets, divide standardized returns by standard conditional deviations and use the following equation:

$$p_{i,j,t+1} = \frac{q_{i,j,t+1}}{\sqrt{q_{i,i,t} q_{j,j,t+1}}} \tag{5}$$

The exponential technique or the GARCH model can be used to determine the dynamic conditional covariance $q_{i,j,t+1}$

$$q_{11,t} = (1-\lambda)(z_{1,t-1} z_{1,t-1}) + \lambda q_{11,t-1} \tag{6}$$

$$q_{22,t} = (1-\lambda)(z_{2,t-1} z_{2,t-2}) + \lambda q_{22,t-2} \tag{7}$$

$$q_{12} = (1-\lambda)(z_{1,t-1} z_{2,t-1}) + \lambda q_{12,t-1} \tag{8}$$

The equation presented below is utilized to derive the dynamic conditional correlation coefficient.

$$p_{12,t} = \frac{q_{12,t}}{\sqrt{q_{11,t} q_{22,t}}} \tag{9}$$

In this research, we sought to expand FAMA's market efficiency theory by examining the mutual effects of two market leadership indexes and a market index. This is the market index of Iran's the exchange rate used by traders (not the official rate), which is the leading index of the market in studies of the Iranian currency exchange.

For this purpose, we called the dynamic conditional relationship of the simultaneous days of these two indicators the immediate effects and the dynamic conditional correlation of the market steering index with a lag of one day later, the market index, the controller effect.

As it is clear in the following equation, for measuring history-oriented bias as the opposite point of the expanded definition of market efficiency, two factors, immediate effect, and controller effect, are considered two pillars of market efficiency.

$$History - orientedbias = \frac{dur * AR(1)_1 + dur * AR(1)_2}{2 * (ImmedeiateeffectCOR + ControllereffectCOR)} \tag{10}$$

In the Markov switching model, regime 1 is auto-regressive process in which the current value depends on the preceding value. As a result, the dynamic conditional correlation of the market leadership index (Iran's official currency exchange) and the market index (the exchange rate used by traders) occurs simultaneously. In controller effect, the market leadership index is dynamically correlated with the market index one day later.

3 Finding

To compute the dynamic conditional relationship between the dual time series of Irans the exchange rate used by traders, and the official rate for dollar, we first examined the optimal conditional risk of each applying the GARCH family. Table 1 shows the results of optimizing GARCH (1,1) for both series. Anywhere coef-

Table 1: GARCH

	The exchange rate used by traders	P-value	Iran official currency exchange market	P-value
		GARCH		
A	0.08*	0.041	0.9*	0
B	0.81*	0	0.48*	0
		GJRGARCH		
A	-0.04	0.05	0.78*	0
B	1*	0	0.49*	0
Δ	0.01	0.8	0.27	0.333
		EGARCH		
A	0.31*	0.02	0.96*	0
B	0.89*	0	0.91*	0
Δ	-0.02	0.818	-0.09^*	0.3233
		PGARCH		
A	0.01	0.688	0.9*	0
B	0.98*	0	0.5*	0
Δ	0.95	0.18	0.07	0.425
Δ	0.3	0.865	1.9*	0.018

ficients α, β, and γ are significant. The symbol $*$ denotes significance at the 5% levels. We use the ARIMA model to measure the efficient market hypothesis using the Markov switching model. Equally shown in Table 2, AR (1) coefficient was significant only in regime 2 at 28% with a duration of 70%. According to Table 3, a

Table 2: Controller Effect, Controlled Effect, Immediate Effect

	AR (1)	Duration	P Value
Regime 1	0.16	0.3	0.38
Regime 2	0.28	0.7	0.015

quantitative calculation can be performed by adding the history-oriented bias of AR

(1) coefficient of the Markov switching model to the immediate effect, or dynamic conditional correlations of the two indices on corresponding days. Iran's exchange rate used by traders, and the official rate were analyzed using equation 11 for the controller effect or a dynamic conditional correlation of Iran's currency exchange index and the lag of Iran's dollar-trader rate market one day later. In this research,

Table 3: History-Oriented Bias

Immediate effect	Controller effect	Controlled effect	History-oriented Bias
48	17	35	0.15

we sought to show the mutual effects of two markets, the exchange rate used by traders, and the official rate, on each other at the same time and with a one-day lag. As shown in Figure 1, the average dynamic conditional correlation between 2 rates at the same time was 48% (market efficiency), and dynamic conditional correlation of 2 rates one day later was approximately 35% (controlled effect), and the dynamic conditional correlation of the Iranian currency exchange market with the exchange rate used by traders one day later was almost 17% (controller effect). In other words, as shown in Figure 1, in most cases, the dynamic conditional correlation of dual simultaneous time series was higher than the dynamic conditional correlation with a one-day interval, which indicates the presence of rapid information circulation in the Iran currency exchange market. So, we can infer that when two series are the same in terms of time, i.e., market efficiency, the Iran currency exchange market has relative efficiency. It can also be argued that when the dynamic conditional correlation of the Iran currency exchange market with the series of the next day, the exchange rate used by traders, not the official rate, i.e., the controller effect, was higher, the exchange rate used by traders was more affected than Iran currency exchange dollar. It was found that Iran's trader rate had a greater impact on exchange market when the dynamic conditional correlation between the Iran currency exchange market series one day later was higher.

4 Conclusions and suggestions

In recent years, the Central Bank of Iran has tried to reduce the volume of currency exchanges in non-toxic markets by establishing an official market for currency exchange (Iran currency exchange). Market efficiency and behavioral finance are the two important paradigms of financial markets, including the stock exchange, exchange market, etc. The dual exchange rate system in Iran (the exchange rate used by traders, and not the official rate) introduces complexities for businesses, creates economic distortions, and could pose challenges for the successful launch and adoption of a CBDC in the future. In fact, Launching a CBDC requires a stable and transparent economic environment. The existence of dual exchange rates may

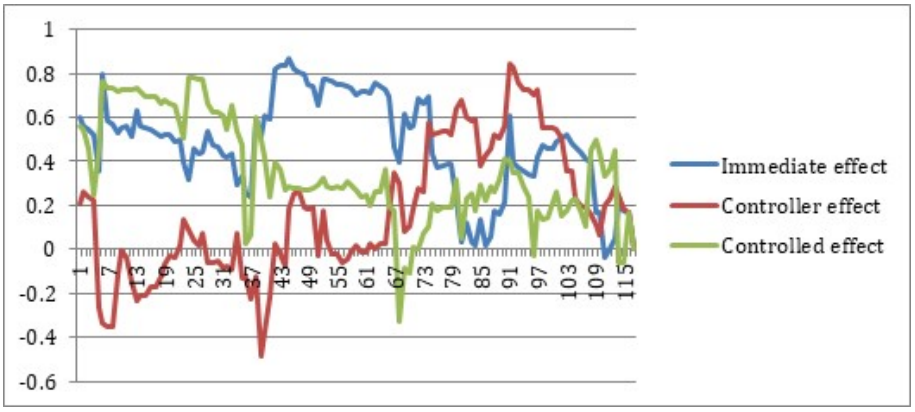

Figure 1: The dollar trader rate market (not official rate) is in a dynamic conditional relationship with the Iranian currency exchange market at the same time and at a daily interval.

raise concerns about the effectiveness of monetary policies, potentially impacting the successful implementation and acceptance of a CBDC.

The aim of this study was to expand the theory of Fama market efficiency and invent a new model to define its opposite point, called history-oriented bias. For this purpose, in addition to measuring the speed of information circulation with the ARIMA model and the Markov switching model for investigating the origin of the effect of the Iran currency exchange market on Iran's dollar trader rate (not official rate), the dynamic conditional correlation of these two-time series was investigated simultaneously and with a one-day lag. Therefore, we investigated the convergence of the Iran currency exchange market dollar with Iran's trader rate exchange market in the period from June 20 to October 30, 2022. Results showed that immediate effect, i.e., dual series simultaneously, had 48% dynamic conditional correlation, on the other hand, controller effect, i.e., the dynamic conditional correlation of 17% of the Iran currency exchange market with one-day later Iran's trader rate (not official rate) market, and controlled effect, i.e., the dynamic conditional correlation of 35% of Iran's trader rate market with the one-day later series of the Iran currency exchange market, were 35%. These findings indicate the 15% history-oriented (or past-oriented) bias of the Iranian currency exchange market. The study findings indicate that, in line with Fama's market efficiency theory, there exists a substantial 15% historical bias in the foreign exchange market in Iran. This bias is noteworthy and could pose a significant challenge for the introduction of Central Bank Digital Currency (CBDC) in the country.

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6 Declarations

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