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Trading volume and Volatility in the foreign exchange market: Application of the GARCH and EGARCH Models

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« The ancient and honorable field of international finance has grown furiously of late in activity, in content, and in scope »

Michael R. Darby

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Rihab Mechmech

Abstract

This study provides a market-microstructure analysis of the exchange rate dynamics using GARCH modeling framework. To analyze major currency pairs, EUR/TND and USD/TND, we focus on the relationship between the exchange rate returns, trading volume and volatility. The study highlights the phenomenon of volatility clustering, suggesting that high volatility periods are often clustered together. We find a unidirectional, causal link running from returns to trading volume, underscoring how volume is often a consequence of returns, rather than a direct cause. The results indicate that the trading volume is insignificant in explaining the exchange rate returns; these findings can be attributed to the market's lack of dynamism, regulatory interventions and the cyclical balance of payments. Furthermore, The results show that the trading volume can be utilized to identify the future volatility state indicating that intensified trading may lead to higher market volatility.

Keywords: Exchange rates returns, Trading volume, Volatility, Microstructure, GARCH, EGARCH, Unidirectional causal link, Volatility clustering.

Résumé

Cette étude propose une analyse de la microstructure du marché des changes à l'aide du cadre de modélisation GARCH. Pour analyser les paires de devises majeures, EUR/TND et USD/TND, nous nous concentrons sur la relation entre les rendements des taux de change, le volume de transactions et la volatilité. L'étude met en évidence le phénomène de regroupement de la volatilité, Ce qui suggère que les périodes de forte volatilité sont souvent regroupées ensemble. Nous identifions un lien causal unidirectionnel allant des rendements au volume des transactions, soulignant comment le volume est souvent une conséquence des rendements, plutôt qu'une cause directe. Les résultats indiquent que le volume des transactions est insignifiant pour expliquer les rendements des taux de change ; ces constatations peuvent être attribuées au manque de dynamisme du marché, aux interventions réglementaires et à l'équilibre cyclique des paiements. De plus, les résultats démontrent que le volume des transactions peut être utilisé pour identifier l'état futur de la volatilité, indiquant ainsi qu'une intensification des échanges pourrait entraîner une volatilité accrue sur le marché.

Mots-clés : Rendements des taux de change, Volume de transactions, Volatilité, Microstructure, GARCH, EGARCH, Relation causale unidirectionnelle, Regroupement de la volatilité.

ABBREVIATIONS

ADF	Augmented-Dickey Fuller Test
ARCH	The autoregressive conditional heteroskedasticity
ARMA	Autoregressive moving average model
CBT	Central Bank of Tunisia
FED	The Federal Reserve
ECB	The European Central Bank
EGARCH	Exponential generalized autoregressive conditional heteroscedastic
FIGARCH	Fractionally Integrated GARCH
FOREX	The foreign exchange market
GARCH	Generalized AutoRegressive Conditional Heteroskedasticity
GJR-GARCH	Glosten, Jagannathan and Runkle GARCH
HFT	High frequency trading
IGARCH	Integrated Generalized Autoregressive Conditional Heteroscedasticity
IGARCH	Integrated GARCH
OTC	Over-the-counter market
SWIFT	The Society for Worldwide Interbank Financial Telecommunications

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INTRODUCTION

Empirical studies of macroeconomic models have proven to be less relevant in the theory of international finance for explaining short-term exchange rate dynamics. To address the shortcomings of these models, researchers in international finance have shifted their focus towards the institutional and organizational characteristics of foreign exchange markets to explain exchange rate dynamics. This new approach is called the microstructure of foreign exchange markets.

To understand how the market reaches informational efficiency, microstructure theory focuses on interpreting the mechanism by which information held by an agent is integrated. In this regard, the main difference between microstructure and macroeconomic approaches lies in the role of traders in price determination. From a macroeconomic perspective, traders play no role in price determination. As a result, recent empirical research in the microstructure of foreign exchange markets has developed models that examine the presence of informed and uninformed traders. Indeed, the study of information, under this new approach, has been developed in two stages. In the first stage, empirical research focused on reexamining the impact of the arrival of macroeconomic public information on the exchange rate. Subsequently, information asymmetry was addressed by considering the connection between the trading volume and the exchange rate.

The microstructure approach focuses on the institutional and organizational characteristics of the foreign exchange market, the resulting interaction among different participants, and the impact they have on price movements. It utilizes new explanatory variables for exchange rate dynamics, such as trading volume, volatility, order flows, and Bid-Ask spreads, instead of the macroeconomic fundamentals used in the macroeconomic approach, such as inflation, interest rates, etc.

The primary objective of microstructure theory revolves around price formation. In this sense, the proposed problem aims to evaluate the contribution of the microstructure theory in the foreign exchange market. Through our research, we will seek to provide an answer to the following question: “To what extent can the microstructure theory, through variables such as volatility and trading volume, contribute to understanding exchange rate dynamics?”

To address this issue, we employ both GARCH and EGARCH models to assess the persistence of volatility and examine the relationship between exchange rate returns and volume. The GARCH model is particularly advantageous for capturing the time-dependent nature of volatility, making it suitable for modeling financial data with varying levels of risk. On the other hand, the EGARCH model, which incorporates asymmetry in volatility responses, is valuable for uncovering the impact of past shocks on future volatility, providing a more nuanced understanding of how external factors influence exchange rate dynamics. These two modeling approaches together offer a comprehensive analysis of the relationship between exchange rate returns and their associated volume.

This thesis contributes to the literature in a number of ways. Firstly, our research question addresses practical implications of great significance, regarding concerns shared by investors and policymakers regarding evolving market dynamics. Secondly, our study distinguishes itself from previous research, which primarily reported on the causal relationship between volume and exchange returns in the Tunisian foreign exchange market. Finally, this paper enriches the microstructure approach to exchange rate research by closely examining exchange rate behavior in Tunisia, with a particular focus on the impact of trading volume and volatility on exchange rate dynamics.

The remainder of the thesis is outlined as follows: The theoretical Part presents the main concepts of this work related the Dynamics of Exchange Rates, the Contribution of Microstructure and an overview of the existing literature regarding the interplay between the exchange returns, trading volume and volatility. The empirical analysis is carried out in the second part, we'll try to highlight the relationship between the trading volume and the volatility as we introduce the GARCH methodology and the equations characterising every variable of our model. The empirical support for our study consists of a series of data on the EUR/TND and USD/TND exchange rates, as well as corresponding volume series. Finally, we conclude our work by presenting a summary of the main findings and implications of our study.

THEORETICAL PART

Chapter 1: Dynamics of the Exchange Rates

1. Introduction

Currency market fluctuations cannot be predicted in the short term only by fundamental theoretical models. The disconnect between exchange rates and fundamental determinants is one of the enigmas of international finance. Indeed, the work of Meese & Rogof (1983) showed the inability of macroeconomic exchange rate models to outclass a simple random process, essentially in the short and medium term. In addition to their weak predictive power, traditional exchange rate determination models are based on simplifying assumptions that deviate from reality. Early research on exchange rate dynamics based primarily on economic aggregates and public information did not consider private information and all aspects of financial market microstructure. This observation was confirmed by the studies of Frankel & Rose (1995) which explain that the most important determinants of the exchange rate are not macroeconomic.

Thus, faced with this disconnection, several researchers have turned to other variables which constitute to integrate the institutional or organizational characteristics of the foreign exchange market in the explanation of the dynamics of exchange thus giving rise to a new approach called microstructure.

Indeed, the transition from the macro-economic approach to the microstructure approach has highlighted two variables which were previously neglected and which constitute the contribution of the approach and lead to a new understanding of the behavior of the exchange rate. These are trading volume and volatility.

We devote this chapter to demonstrating the structure of the Tunisian foreign exchange market, exploring exchange rate dynamics and characteristics, and delving into other related concepts.

2. The Structure of Foreign Exchange Market

The microstructure approach is an attempt to introduce variables, neglected by macroeconomic models, including information structure, participants behavior and the role of institutional structure in the short-term dynamics of institutional structure of exchange rates.

This section will attempt to present the specific features and characteristics of the Tunisian market.

2.1. The characteristics of the foreign exchange market

The foreign exchange market is the place where supply and demand for currencies are confronted. This market includes spot foreign exchange (spot) rates but also forward foreign exchange (in different forms) rates and therefore implies access to treasury transactions (loan/borrowing) in foreign currency or in national currency. In addition, for several years a new type of market has appeared, the so-called market for derivative instruments (or products).

The characteristics of the foreign exchange market

- A continuous and decentralized market.
- An over-the-counter (OTC) market.
- A quasi-perfect market.
- A market governed by prices.
- A market dominated by banks.

2.1.1. A continuous and decentralized market

Unlike other markets, the forex market is not a “physical” place. It has no centralized structure and transactions are concluded from one country to another through very rapid means of communication.

2.1.2. An over-the-counter (OTC) market

The foreign exchange market is primarily an over-the-counter (OTC) market. In fact, exchanges predominantly occur at the interbank level, and there is no centralized quotation system like in a stock exchange. At a given moment, divergences can occur from one location to another and also from one bank to another within the same location.

2.1.3. A quasi-perfect market

Indeed, it is generally accepted that in the foreign exchange market, each participant has free access to information that could have an impact on the fluctuation of exchange rates.

2.1.4. A market governed by prices

A price is communicated before any transaction takes place. The party requesting the price has the option to choose whether or not to trade with their counterparty on either the buy or sell side. Participants who are accustomed to quoting prices make up a category called 'market makers'. They commit to executing trades at the prices they display as soon as a counterparty requests it.

2.1.5. A market dominated by banks

The participants operating in the foreign exchange market can be categorized into three different groups: the first consists of corporations, fund managers, and individuals; the second includes monetary authorities (central banks); and the third comprises banks and brokers who facilitate the day-to-day functioning of the market.

2.2. Market participants

The foreign exchange market is a decentralized market in which different actors, each with their own needs, interests, and motivations, engage in exchanges with one another. These different actors can be categorized into six categories:

2.2.1. Central Banks

Central Banks play a key role in the foreign exchange market. Their influence in this market stems not only from their role as a party to a transaction but also, and perhaps more importantly, from the policies they intend to pursue. The primary objectives of Central Banks are to control the money supply and inflation while ensuring economic growth and monetary stability. The foreign currency reserves held by Central Banks are one of the tools they use to pursue these objectives.

2.2.2. Commercial Banks

Commercial Banks are the most important actors in the foreign exchange market. Transactions between banks not only constitute the majority of commercial turnover but also represent a significant portion of speculative transactions.

2.2.3. Brokerage Firms

These financial institutions execute operations with international fund portfolios, buying foreign currencies to secure guaranteed profits for their clients. The foreign exchange transactions they carry out mainly involve trading activities related to investment funds, international companies, and money market funds.

2.2.4. Hedge Funds

Private investment funds that employ various strategies to speculate in the foreign exchange market. Due to their large reserves of liquidity, trading strategies, and significant leverage they utilize, hedge funds play a major role in the market.

2.2.5. Commercial and Industrial Companies

Importers and exporters are exposed to the risks of currency fluctuations, so they use the foreign exchange market to hedge themselves against such risks by securing future cash flows and protecting themselves against currency fluctuations. Their primary objective is usually not to profit from speculation on these variations but rather to avoid potential losses.

2.2.6. Individuals

These are individuals who use the foreign exchange market to meet a need for currency, such as tourists traveling abroad.

These different actors, through their interactions, ensure the functioning and sustainability of the foreign exchange market.

2.3. The Tunisian Foreign Exchange Market

The Tunisian foreign exchange market is exclusively interbank, as only banks have access to it, along with a few companies for specific operations. Non-banking financial institutions and private customers do not have access to it. To understand the Tunisian foreign exchange market, we will present its history, its segments, and its evolution.

2.3.1. Historical Background

As part of Tunisia's economic liberalization, numerous reforms and laws have impacted its financial system. In fact, following the gradual liberalization of the exchange rate regime and foreign trade, two additional steps were necessary to establish a foreign exchange market that would fully play its role in the economic system.

The first step was the establishment of a currency market introduced by Circulars 89.18 dated May 17, 1989. These new measures were implemented to bring flexibility to the payment system and exchange rate regime in Tunisia. This market allows banks to manage the currencies of their resident and non-resident clients without prior authorization from the Central Bank of Tunisia.

The second conditional step towards establishing the foreign exchange market was the current convertibility of the Tunisian dinar. This reform ensures the dynamic integration of the Tunisian economy into the global economic space as it allows for the settlement of current transactions through the purchase or sale of foreign currencies against Tunisian dinars without prior authorization and at a market-determined exchange rate. This convertibility is designed to encourage exports as a solution to the limited domestic market and to further promote foreign investments as a solution to the insufficient national savings. It was in December 1992 that the current convertibility of the Tunisian dinar was officially announced by presidential decision, wherein the exchange rate of the dinar is no longer fixed by the Central Bank of Tunisia (CBT) but determined by market mechanisms.

This convertibility contributes to:

- Increased foreign competition by lifting restrictions on foreign exchange operations and encouraging businesses to enhance their competitiveness.
- The free movement of capital, which attracts foreign investment when the exchange rate is relatively stable. The major risk of convertibility and the removal of exchange controls lies in the potential outflow of foreign capital caused by market instability. Therefore, the convertibility of the Tunisian dinar applies only to current transactions.

Two years after the establishment of the current convertibility of the Tunisian dinar, the financial authorities created an interbank spot foreign exchange market in which exchange rates would be determined by the supply and demand of currencies. This was enacted by the law in March 1994. Up until this point, the Central Bank of Tunisia (CBT) had a monopoly on setting exchange rates for the dinar against foreign currencies.

Currently, the dinar is quoted throughout the day, considering the volatility of exchange rates in international financial markets and The degree of liquidity for individual currencies within the Tunisian interbank foreign exchange market. The Central Bank acts as the market regulator by controlling its liquidity. However, in order to manage the risks associated with foreign exchange activities, the CBT establishes a long-term reference rate while leaving the determination of spot rates in the hands of the interbank foreign exchange market. The CBT intervenes only when it observes a persistent deviation of exchange rates from the reference rate. This intervention involves providing banks with the necessary liquidity to ensure the supply and demand of currencies are aligned.

On May 31,2021, the Central Bank of Tunisia published two new circulars on the organization and operation of domestic foreign exchange markets, and on hedging instruments against foreign exchange, interest rate and commodity price risks.

- Circular 2021-02, which covers the use of hedging instruments against exchange and interest rate risks and hedging against commodity price fluctuations.

  Approved Intermediaries are authorized to enter into currency swaps with each other in the form of currency/dinar and currency/currency in order to hedge the foreign exchange risk incurred on the portfolio of currency swaps entered into with their customers.

  Approved Intermediaries are authorized to enter into currency swap transactions with foreign financial institutions in order to hedge the foreign exchange risk on currency swap portfolios entered into with their customers, in compliance with the rules set out in Title V of the circular relating to risk management rules.

- Circular 2021-03 on the organization and operating rules of domestic foreign exchange markets. For example, foreign exchange and money market transactions in foreign currencies, including hedging transactions, between Approved Intermediaries must be carried out via the Refinitiv Dealing system and/or the Bloomberg system. Approved Intermediaries choosing to use the Refinitiv Dealing system exclusively or in parallel with the Bloomberg system must install the "Trade Reporting" solution supplied by Refinitiv. Authorised Intermediaries choosing to use the Bloomberg system must authorize Bloomberg to allow the central bank to consult the transactions carried out on this platform.

The main contributions of these two circulars are as follows:

- Harmonization, both in terms of operation and risk management rules, of the provisions of the previous circulars on the operation of domestic foreign exchange markets, namely circular n°2016-01 of February 8, 2016, circular n°92-13 of June 10, 1992 and circular n°97-08 of May 9, 1997;
- Expansion of the range of hedging instruments available through the introduction of new instruments to hedge against currency and long-term interest rate risks (Cross Currency Swap-CCS & Interest Rate Swap-IRS), as well as against the risk of fluctuating commodity prices;

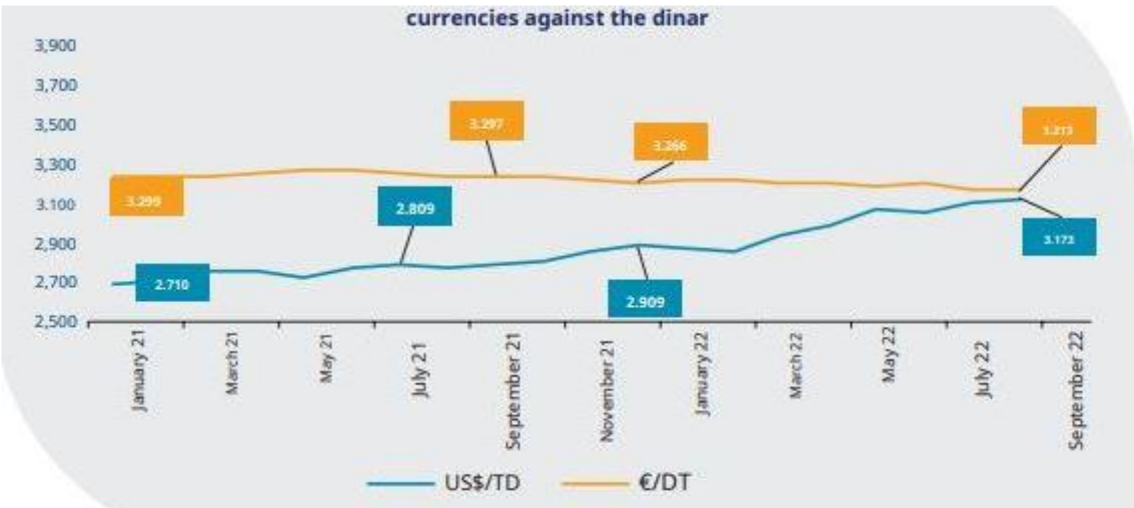
- Extend the scope of use of hedging instruments to the dinar for interest-rate risk, and to other currencies for exchange-rate risk;
- Allowing authorized intermediaries to hedge their exposure to foreign exchange and interest rate risks, generated by their hedging operations with customers, through replicating operations.

2.3.2. The dynamics of the Tunisian Foreign Exchange market

The Tunisian central bank has published that « In late 2022, the Tunisian dinar recorded a decrease of 7.2% against the dollar and 0.9% against the euro in the interbank market. Nevertheless, the dinar increased by 5.6% against the Moroccan dirham and 7% against the yen »[1].

Simultaneously, « the euro decreased by 5,9% against the dollar. As for the annual averages, in the year 2022, the dinar experienced an increase of 9,9% against the dollar, 8% against the Japanese yen while it decreased by 1,1% against the Euro ».

Figure 1:Evolution of the exchange rates of the main currencies against the dinar



Source: annual report BIAT

We can observe contrasting trends in the dinar's exchange rate against major currencies: a decrease in the dinar's value concerning the USD while experiencing an increase concerning

1 CBT

the Euro. This disparity can be attributed to the differing monetary policies pursued by the Federal Reserve (FED) and the European Central Bank (ECB).

The divergent paths taken by these central banks have substantial implications for the exchange rates, contributing to the observed dynamics in the currency market.

Table 1:Evolution of the volume of transactions broken down by type of participant

Designation	**2018**	**2019**	**2020**	**2021**	**2022**
Market Interbank	18934,8	13025,6	17055,7	13984,6	15711,8
Resident banks	17690,4	10134,0	13848,1	12047,8	13751,4
Off-shore banks	1244,4	2891,6	3207,6	1936,8	1960,4
Central bank	13732,0	8646,5	5434,3	5823	4689,2
Total	**32666,8**	**21672,1**	**22490**	**19807,6**	**20401,0**

Source: CBT statistics

The table exhibits a domination of the interbank market, and an average of interventions of the Central Bank of Tunisia during these five years. Indeed, since the 1990s and until 2000, the exchange policy followed, within the framework of a financial liberalization plan, led to the stabilization of the real effective exchange rate of the Tunisian dinar. The abandonment of this policy from 2001, combined with the rise in power of the Tunisian interbank foreign exchange market and the reduction in the intervention of the central bank of Tunisia, allowed greater flexibility in the exchange rates of the dinar, both real and nominal.

The decline in the dinar's trading volume against the euro and dollar between 2019 and 2022 can be ascribed to several economic aspects, including political instability in Tunisia, the economic slowdown, a deficit trade balance and political conflicts such as the war in Ukraine. Moreover, the COVID-19 pandemic had a major impact on the global economy, leading to doubts on the financial markets, which may have discouraged investors and caused a decline in the dinar’s trading volume in support of safer assets.

2.4. The effects of the COVID-19 Pandemic and Russia-Ukraine Conflict on the Foreign Exchange Market

Over the past four years, the world has experienced two significant crises that unfolded in succession. Firstly, in December 2019, the initial cases of the Coronavirus disease 2019 (COVID-19) were identified in the Wuhan region of China. The situation escalated to the point where, on March 11, 2020, the World Health Organization officially categorized COVID-19 as a global pandemic, declaring it a public health emergency of international concern.

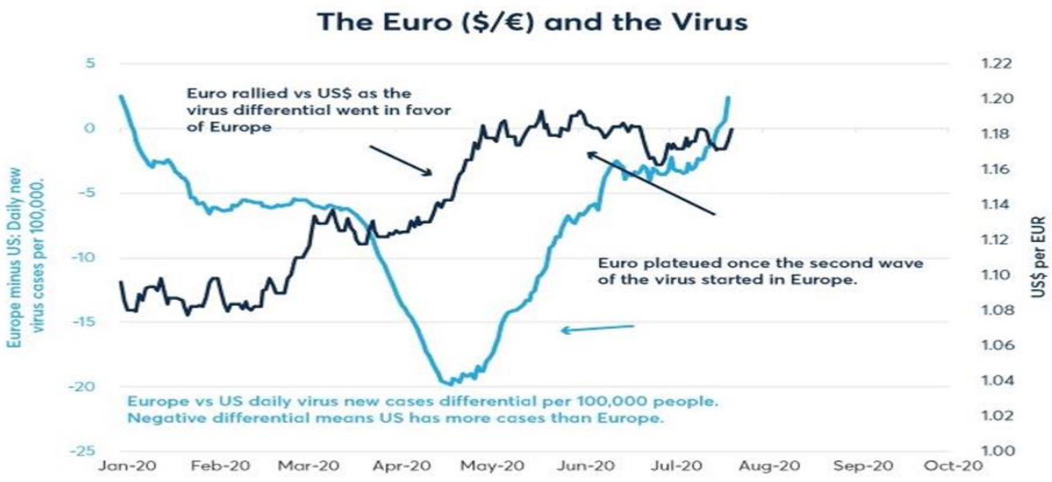
On the other hand, February 2022 Encountered aggravated tensions between Russia and Ukraine, which deeply affected the financial markets around the world. The forex market, too, has witnessed substantial drops. Major currencies like the US dollar, Euro and the Russian currency Ruble have been the most affected.

2.4.1. The Covid-19 pandemic and the foreign exchange market

The COVID-19 pandemic, originating in Wuhan, Hubei, China, has rapidly spread across borders (Liu, Gayle, Wilder-Smith, & Rocklöv, 2020). Unlike typical financial crises resulting from systematic economic shifts, this pandemic has had an unparalleled impact on international financial markets. The distinctiveness of this impact lies in the heightened uncertainties regarding both the consequences and the duration of the pandemic. This has decelerated the economic and commercial activity, and encouraged governments to engage in numerous policy and interventions, to manage a potential long-term recession.

The pandemic's impact on the global economy can be categorized into three main dimensions. Firstly, the widespread implementation of isolation measures has immediately disrupted international trade, leading to a significant reduction in trade volume. Secondly, financial markets and stock markets worldwide have experienced substantial declines, with many major stock markets losing a significant portion of their value. Additionally, central banks like the European Central Bank and the Federal Reserve have introduced extensive financial aid and lowered interest rates to mitigate the economic effects of lockdowns. These dimensions collectively affect the macroeconomic, monetary, and financial aspects of economic activity.Consequently, the fundamental factors influencing the exchange rates of major currencies, such as the U.S. dollar and the euro, have been substantially impacted by the COVID-19 pandemic.

Figure 2: Euro exchange rate from January 2020 to October 2020



Source: Bloomberg

At the onset of the pandemic, the Euro found itself in a position of relative weakness compared to the US dollar. Europe, particularly countries like Italy, bore the initial brunt of the virus's impact well before it reached the United States. However, an intriguing shift occurred between March 2020 and the end of August, during which the Euro's value appreciated by more than 10% against the US dollar. This upward trajectory was a notable departure from the initial trend. Nonetheless, this ascent was eventually curtailed as mounting evidence of a second wave of the virus began to surface. The anticipation of a potentially detrimental economic impact stemming from this second wave prompted the Euro's upward trajectory to stall.

This sequence of events highlights the relationship between the currency markets and the unfolding global health crisis. It underscores how shifts in the perceived severity and trajectory of the pandemic can swiftly influence currency dynamics, reflecting both economic expectations and risk assessments on the part of investors and traders.

In Tunisia, the exchange rate of the dinar has stayed resilient against foreign currencies during the COVID-19 crisis. This crisis has led to a recession in the value of exports and the suspension of the tourism sector, which are considered the major providers of foreign currency in Tunisia. The dinar has remained relatively stable for two reasons, as explained by the economic expert Mohsen Hassan.

Firstly, Tunisia had established a substantial reserve of foreign currency. This reserve was primarily sourced from the revenues generated by the flourishing tourism sector in pre-pandemic times. Additionally, donations and credits injected additional support into this reserve, further fortifying the dinar's stability. The second reason behind the dinar's steadfastness was the turmoil gripping the global financial markets. These markets were marked by volatility and unpredictability in the valuations of foreign currencies. In the midst of this financial upheaval, the dinar emerged as a beacon of stability. While other currencies grappled with fluctuations, Tunisia's dinar held its ground. This stability became all the more pronounced in a time when global economic uncertainty was the norm.

2.4.2. The Russian-Ukrainian war and the foreign exchange market

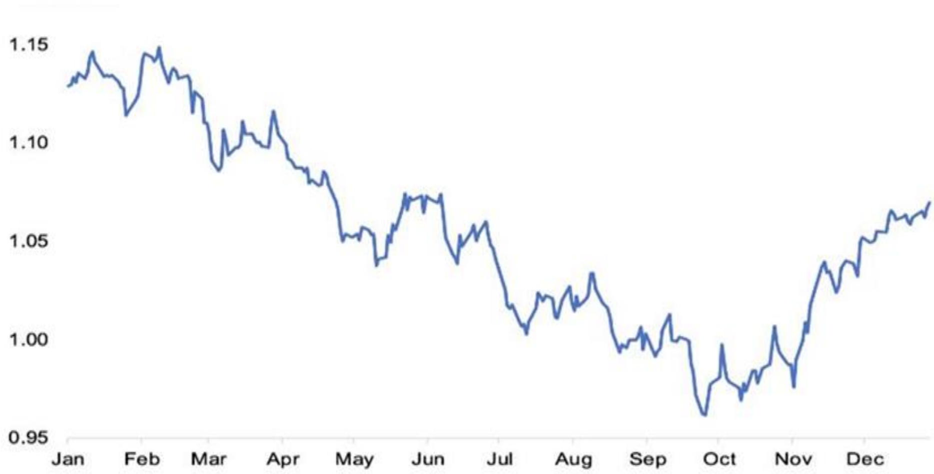
The Forex market witnessed an increased volatility amid the conflict. the negative impact on European economic growth led to a lack of confidence in the euro. The downward trend of the euro against the dollar, which has been ongoing for nearly a year, has increased since the war. This can be explained by two main reasons.

The first factor is related to the high level of uncertainty caused by the conflict, resulting in significant volatility in financial markets, particularly in the foreign exchange markets. Trading at a rate of 1 euro to 1.087 dollars on March 8, 2022, The Euro hit its lowest point against the US dollar in nearly two years, occurring on May 25, 2020, at the peak of the COVID-19 crisis.

This decline is a result of investors losing confidence in the Euro, opting for the stability offered by the US dollar, a globally recognized safe-haven currency. The US dollar is favored for its liquidity and ease of trade, attracting investors during uncertain times. The ongoing conflict situation only reinforces this preference, leading investors to divest from Euro-based investments. Furthermore, recent sanctions targeting major Russian banks' access to the international interbank payment system, SWIFT, and the freezing of the foreign assets of the Central Bank of Russia, have amplified the demand for the US dollar, further solidifying its strength against the Euro.

The second factor linked to European economic sanctions penalizing the Russian gas and oil exports, the global supply of hydrocarbons has been reduced, which led to an increase in energy prices. The impact on the growth of European economies would be significant, much more so than on the US economy, which is less dependent on Russian hydrocarbons and is one of the world's main hydrocarbon production regions. The possibility of inactive economic growth in Europe increases investor pessimism towards the euro, pressing its value downward.

Figure 3:USD/EUR spot exchange rate in 2022



Source: The Centre for Economic Policy Research

Looking at the USD/EUR evolution, The Euro's decline and the shift towards the US dollar stem from various factors, with Europe's geographical proximity to the conflict zone and its reliance on Russian hydrocarbons being key contributors. Two primary reasons underpin the Euro's depreciation against the dollar.

Firstly, the ongoing Russia-Ukraine conflict has created an atmosphere of uncertainty in the Forex market, eroding trust in the Euro and bolstering the preference for the US dollar. As a globally dominant reserve currency, the US dollar is exceptionally liquid and easily tradable, making it an attractive choice for investors seeking stability during turbulent times. It is regarded as a safe-haven currency, particularly amid global economic uncertainty. The escalation of the conflict only exacerbates the withdrawal of investors from Euro-denominated assets.

Furthermore, the imposition of sanctions, such as the exclusion of numerous Russian banks from the SWIFT payment system, effectively cutting off financial transactions with Russia, has heightened the demand for the US dollar. This, in turn, has fortified the dollar's standing against the European currency. These combined factors have had a pronounced impact on the Euro's value relative to the US dollar.

3. Conclusion

In conclusion, this chapter has delved into the complexities of Tunisia's foreign exchange market. It has provided a comprehensive historical context and elucidated the functioning of domestic foreign exchange markets. Moreover, it has meticulously examined the evolution of the dinar and major currencies amidst the backdrop of the COVID-19 pandemic and the Russia-Ukraine conflict. These findings underscore the imperative nature of comprehending the determinants of exchange rate fluctuations in Tunisia, essential for making judicious economic decisions in the face of a dynamic global economic landscape.

Chapter 2: The emergence of FX microstructure

1. Introduction

The main aim of the microstructure theory is to understand and analyze the mechanisms of price formation and to model the Forex in a way that was radically different from the traditional macroeconomic approach.

In this chapter, we delve into the historical evolution and emergence of the microstructure approach. We trace its roots and analyze its development over time. Our focus then shifts to the key features that set this theory apart, providing a lens through which we can explore the Forex market's dynamics. By delving into these characteristics, this chapter aims to offer a profound understanding of how this approach enriches our comprehension of exchange rate dynamics.

2. The emergence of the microstructure approach

Meese and Rogof (1983) and other authors state that the macroeconomic approach to the exchange rate have failed empirically. In this context, Fankel and Rose (1995) claim that no fundamentals model explains or predicts the exchange rate movements, in the medium and short term. Similarly, Evans and Lyons (2004) claim these traditional models cannot outperform a random walk.

At this point, a question arises: If the determinants of the exchange rate are not macroeconomic, such as fluctuations in interest rates or inflation, what could they be? Two different alternatives provide an answer to this question:

The first supported by authors such as Blanchard, Meese and Evans (1989). In their studies the authors state that the determinants of the exchange rate include variables are typically modeled by rational speculative bubbles.

However, Flood and Hodrick (1990) claim that the rational bubbles is not convincing. This claim was supported by Hau (1998) who shed light on irrationality in financial market: this approach studies the fact that exchange rates can be determined in part by the market participant behavior. Finally, Frankel and Rose (1995) highlight that the macroeconomic variables have a weak ability to predict the exchange rate fluctuations.

Therefore, a new approach has appeared: the Microstructure theory.

2.1. Definition of microstructure

The microstructure of foreign exchange market seeks to better understand the information implanted in order flows, which directly influences the dynamic processes of price fluctuations. This approach has outperformed macroeconomic models, especially markets are inefficient; more precisely, not all agents and players on the foreign exchange have access to the same information, let alone the same motivations and objectives.

Maureen O'Hara (1995) defines microstructure as « The process and outcomes of exchanging assets under explicit trading rules ».

The response of the microstructure approach to the dominant macroeconomic approach has been essentially on the basis of realistic hypothesis that allow us to understand the complexity of exchange rate dynamics:

- H_1: The existence of information relevancy to the determination of the exchange rate which is not publicly available, and thus the existence of private information most often through order flow.
- H_2: Participant heterogeneity influences the price and the price formation.
- H_3: The exchange mechanism has an impact on the price formation processing.

Moving from the macroeconomic to the microstructure approach, three variables that played no role in the macroeconomic approach become important.

These variables are the trading volume, volatility, order flow, bid-ask spreads.

2.2. The trading volume

Volume in the forex market refers to the number of lots traded on a currency pair during a specific period. In other words, it represents the quantity of currencies bought and sold.

Volume is also related to market liquidity, which is the ease with which currencies can be bought or sold. When trader volume is high in the market, it's more likely that you can open and close positions quickly and with narrower spreads. Major currency pairs have the highest volumes and, therefore, enjoy the greatest liquidity.

A currency pair with low volume means it will be less liquid because fewer traders are buying and selling the currency. This is typically the case with minor and exotic currency pairs.

Trading volume in the foreign exchange market plays a significant role in influencing prices. This happens because it reflects the existence of different expectations among market participants. There are two main theories that help explain why trading volume is important.

The first one is called the "uncertainty theory." It suggests that when there's a lot of trading activity, it means that information is spreading quickly among traders. In other words, high trading volume can be a sign of rapid information exchange.

The second theory is known as the "Hot Potato" theory. It's a bit different. This theory says that when there's a lot of trading, it doesn't necessarily mean there's a lot of valuable information changing hands. Instead, it's like traders are passing a "hot potato" to each other, trying to avoid risk.

In practice, when a trader receives a substantial order from a client, retaining the entire order could expose them to excessive risk if the market moves unfavorably. Consequently, they seek to distribute a portion of the order to another trader who is willing to assume the associated risk.

So, trading volume can tell us how information spreads in the market and how traders handle risk. When there's a lot of trading, it's not just about information; it's also about managing risk. That's why trading volume is so important in the foreign exchange market.

2.3. Volatility

In the field of finance, volatility is a latent and unobservable variable that needs to be calculated to indicate the extent of fluctuations in the value of an asset over a defined period. The volatility of an asset can thus be interpreted as the level of uncertainty associated with it. It is an extremely important variable for decision-making in terms of investments and the determination of an asset's price, particularly for derivative products. For global financial institutions, predicting future volatility is essential to assess their current vulnerability.

In the foreign exchange market, volatility is a highly significant factor for the vast majority of local and international businesses, as well as for the economies of countries where the value of their currency is determined by the market. Companies actively manage the risk associated with FX market volatility, as it presents an additional risk. This is because they often deal with multiple currencies or various assets tied to different currencies to conduct their operations (Muff, Diacon & Woods, 2008). If an international company does not hedge against volatility risk, several financial metrics such as assets, liabilities, and net profit can be directly affected, either positively or negatively.

Excessively high volatility can also be detrimental to a country's economic performance. It can indirectly lead to a decrease in domestic consumption (Bahmani-Oskooee & Xi, 2011) and negatively impact productivity growth (Aghion, Bacchetta, Rancière & Rogoff, 2009). It may have an adverse effect on employment rates among 17 industrialized countries (Feldmann, 2011). Ultimately, volatility can negatively impact investments, particularly in the short term (Bahmani-Oskooee & Hajilee, 2013).

Moreover, volatility provides information about market psychology. High volatility reflects a context of turbulence and uncertainty, making investors wary of financial markets. Low volatility, on the other hand, is synonymous with market stability. It can reflect investor confidence in the market, as well as an environment conducive to growth. Periods of high volatility are periods of higher risk, but also higher reward.

Secondly, volatility plays a significant role in the choice of an investment security. Taking into account the volatility of the stock in question is essential, as the level of risk the investor wishes to bear is intimately linked to that of the stock's volatility. Risk averse investors tend to invest in less volatile, and therefore less risky, assets, while risk taken investors invest more in highly volatile, and therefore very risky, assets. Therefore, market volatility is not constant and cannot be directly observed; often, a GARCH model is used to estimate it.

There are three concepts of volatility. The first is unconditional or historical volatility, which represents the sum of unanticipated volatility. The second concept is, of course volatility being a persistent phenomenon, GARCH models, which postulate a process for volatility behavior, make it possible to isolate the conditional component of volatility. It can then be compared with the third concept, which is the implied volatility of currency options, which is a market forecast that is by nature forward-looking. (Bronka Rzepkowski, 2001).

2.3.1. Historical or unconditional volatility

In this concept, we can distinguish between two measures of historical volatility, simple and weighted. Simple historical volatility is assessed by means of an annualized standard deviation of daily fluctuations in past exchange rates. This measure reflects the unconditional volatility, it means it does not isolate the past volatility on the basis of available information. Historical volatility is therefore an ex-post measure of exchange rate variations. Weighted historical volatility assigns greater weight to the most recent past observations. (Bronka Rzepkowski, 2001).

2.3.2. Conditional volatility

In the past, it was often assumed that volatility remained constant over time. However, by analyzing the returns of an asset, we can observe that the variance tends to differ from one chosen period to another. This concept is known as heteroscedasticity. The current level of volatility is also often influenced by that of previous periods, which is referred to as conditional heteroscedasticity. High volatility periods tend to be observed following other high volatility periods, and similarly, low volatility periods often follow other low volatility periods. The frequencies of observing high or low volatility periods are not stable; high volatility periods are often clustered together, as are low volatility periods. The current variance is thus linked to the variance of previous periods, creating clusters of volatility. This phenomenon is also identified as volatility clustering.

Conditional volatility, often quantified using GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models, serves to capture the persistence observed in financial time series. It characterizes the phenomenon where turbulent periods, marked by significant exchange rate fluctuations, are succeeded by calmer intervals when exchange rates experience only minor fluctuations. This concept was introduced by Engle (1982) and later extended by Bollerslev in 1986. The GARCH (1,1) model, a prevalent specification, offers a versatile framework for representing conditional volatility processes, making it a widely used tool for modeling financial market dynamics.

2.3.3. Implied volatility

In the world of financial trading, particularly in the Over-the-Counter (OTC) market, currency options are typically quoted in terms of implied volatility. Implied volatility is a key metric used to estimate the expected future price fluctuations of a financial instrument, in this case, currency options. Traders utilize this implied volatility figure as an input when applying mathematical models like the Black and Scholes model (developed in 1987) or the Garman and Kohlhagen model (from 1983) to determine the price of currency options.

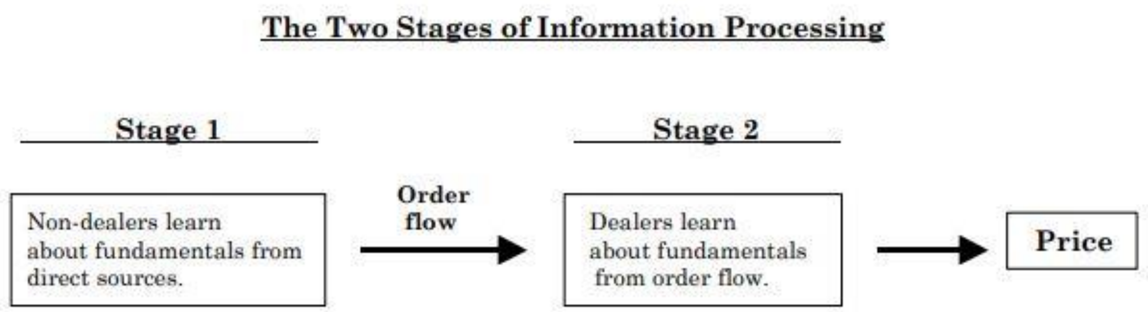
2.4. Order Flow

Understanding order flow is essential to be able to appreciate the difference brought by the microstructure approach compared to the macroeconomic approach it is worth mentioning that trading volume differs from order flow. Order flow is the trading volume that is assigned sign. Order flow is essentially a measure of market activity, calculated as the sum of buy trades with positive signs and sell trades with negative signs. When the result is negative, it indicates a predominance of selling activity, suggesting net selling pressure in the market. Conversely, when the result is positive, it signifies a preponderance of buying activity, reflecting net buying pressure. Essentially, order flow provides insights into the balance between buying and selling within the market, helping analysts understand market sentiment and potential price movements.

Traditional models assume that all market participants have the same information, while the microstructure model recognizes that market participants use different information to form their thoughts. Thus, informed and rational traders exploit this informational advantage by publishing their orders to market makers. The latter by observing the flows, mark inferences on the private information for after adjusting their quotations, in other words, when there is a buy order, the participants must raise the probability that the client has received private information. So, if there is a sell order, in this case it will lower this probability.

Therefore, the predictive capability of this variable in understanding the exchange rate behavior has been discussed by Lyons (2000) and presented diagrammatically as follows:

Figure 4: Information processing of Lyons 2000



Source: Lyons (2000)

The order flow delivers informations concerning the fundamentals, in this sense it represents a transmission mechanism. When the information is available, traders have no interest in analyzing order flow. But in practice, information about the exchange market is not all known by the public, so knowing the order flow is very important.

2.5. Spreads

The spread, an essential concept in microstructure theory, serves as a critical liquidity indicator. It essentially represents the distinction between the ask price (the price at which sellers are willing to sell) and the bid price (the price at which buyers are willing to purchase). This difference serves as a tangible measure of transaction costs in the market.

Microstructure theory, evolving since the work of Demestz in 1968, identifies the spread as the cost associated with achieving immediacy in trading. In simpler terms, it's the compensation provided to market makers for the essential liquidity services they offer.

The spread encapsulates various dimensions of costs in market operations. These include order processing costs, which arise from executing transactions; inventory holding costs, which emerge from maintaining positions; adverse selection costs, often referred to as information costs, arising due to the information asymmetry between traders; and counterpart search costs, which are the costs linked to identifying suitable trading partners. Together, these costs make up the total price range and play a fundamental role in understanding the intricacies of financial markets.

2.5.1. Order processing costs

These costs are delivered by the market makers and generated by the obligation of permanent monitoring of the market, for example staff costs, premises costs, information acquisition costs.

2.5.2. Inventory Holding Costs

This cost comes from holding a currency position that involves a loss of profit. Indeed, the obligation to provide immediate consideration forces the holder to store quantities of unwanted assets and therefore to hold a portfolio whose risk characteristics and degree of diversification do not correspond to an optimal composition. This cost will be incorporated into the range by widening it. The cost of holding inventory is also due to the risk of price volatility as it is sensitive to transaction activity (weekend and holiday effect).

2.5.3. Cost of adverse selection (Information Costs)

It is the cost due to the asymmetry of information, indeed seen that the differentiation between the informed agents and the uninformed agents on the market, the tenor widens his range to compensate for the losses suffered by negotiating with the informed.

2.5.4. Counterparty search cost (Search Costs)

the foreign exchange market, unlike the equity market, is a decentralized market, operators must therefore seek the best counterparty on the market, which induces costs which take the form of price variations due to the revelation of transactions at more than an operator.

3. Conclusion

This chapter provides a comprehensive overview of the transition from traditional macroeconomic viewpoints to the burgeoning field of microstructure theory in the context of foreign exchange markets. It emphasizes how the microstructure approach has revolutionized our understanding of price formation mechanisms, moving beyond traditional macroeconomic models. The central focus is on three distinctive features that set this approach apart: trading volume, volatility estimated by advanced models like GARCH, bid-ask spreads and the order flow. These features offer a deeper understanding the characteristics of the foreign exchange market and how various factors interact to influence price dynamics. By delving into these aspects, this chapter establishes a solid framework for exploring Forex microstructure and its role in shaping market behavior and efficiency.

Chapter 3: Literature review

1. Introduction

The foreign exchange market, distinguished for its high daily trading volume and dynamic nature, has long allured the attention of researchers and market participants. Throughout the years, the study of microstructure theory has emerged as a crucial approach through which to understand the complexities of this dynamic market. By investigating the finer details of price formation, liquidity, volatility and the interplay of market participants, the microstructure approach has untangled essential insights that have significantly changed our perception of forex dynamics.

In this chapter, we explore numerous papers and contemporary results that showcase the profound impact of the microstructure approach to Forex. Throughout the sections of this chapter, we shed light on key discoveries that have shaped the way market participants perceive and navigate the dynamics of the foreign exchange market. From the presentation of market microstructure models that capture the essence of price movements to the exploration of the different relationships that emphasize this theory especially the relationship between the trading volume and the volatility.

2. Transition from Macroeconomic Theory to Microstructure

The macroeconomic models used to explain the formation and evolution of exchange rates, there is often an abstraction of concrete price formation aspects. When equilibrium is determined, the price will automatically be established.

Microstructural exchange rate models are of particular interest to macroeconomists macro economists, as they can explain the short-term dynamics of exchange rates and help to better forecast the evolution of macroeconomic variables that determine economic activity.

The microstructural and macroeconomic approaches are based on very different sets of assumptions. (Fränkel, Galli, and Giovanni, 1996; Lyons, 2001). Macroeconomic models assume that agents are identical, that information is perfect, that there are no transaction costs and that the bargaining process is irrelevant, whereas microstructural exchange rate models make none of these assumptions. By observing its assumptions, the microstructural approach constitutes a response to the violation of the assumptions of the macroeconomic approach:

- The homogeneity of market participants.
- The public availability of information.
- The abandonment of any effect of the exchange mechanisms (Trading).

Traditional exchange rate models make simplifying assumptions like identical agents, perfect information, and no transport costs. These assumptions don't align with reality, leading to the question: Why would identical agents exchange? To address this gap, new models are needed, considering the diversity of agents, imperfect information, and transaction costs. It's crucial to bridge the disparity between theory and reality for a more accurate understanding of exchange rate dynamics.

It's crucial to emphasize that when applying microstructure theory to the foreign exchange market, we go beyond studying the influence of institutions on price formation. More significantly, it delves into analyzing the implications of informational asymmetry in shaping exchange rates. In markets with low transparency, like the foreign exchange market, informational asymmetry has abundant opportunities to manifest. This is evident, for instance, in the unavailability of comprehensive information on the sizes and prices of individual transactions to the entire market. In such an environment, understanding the impact of information imbalances becomes pivotal for comprehending the consequences and complexities of exchange rate dynamics.

Meese and Rogoff (1983) established the groundwork for the microstructure approach, challenging traditional macroeconomic perspectives. Their research demonstrated that a random walk model is as effective as macroeconomic models in explaining exchange rate dynamics, even when using actual, rather than anticipated, fundamental values.

In addition, Meese and Rogoff (1983) examined various structural models rooted in the asset market approach. This framework posits that changes in exchange rates result from transactions in the asset market.

Hamon (1994) posits that microstructure questions the assumption of free, immediate, and unbiased information, focusing on the impact of asymmetric information in the foreign exchange market. Similarly, Lyons (2001) illustrates that microstructure models extend beyond high-frequency data, asserting their relevance in the long term. Economic consensus holds that price movements from new information persist. Therefore, it is crucial to pinpoint information channels and identify agents with access. Microstructure theory delves into the origins of exchange rate movements, particularly scrutinizing the trading floor.

Flood and Rose (1995) assert that nominal exchange rates display notably higher volatility, especially at low frequencies, compared to the macroeconomic variables they are theoretically connected to. This heightened volatility raises questions about the effectiveness of exchange rate models relying on macroeconomic factors to comprehensively clarify or predict the trajectory of nominal exchange rates. This difference suggests the potential omission of crucial variables in traditional exchange rate models. Existing literature proposes various reasons for these oversights, including the impact of unobservable macroeconomic shocks on exchange rates, irrational behavior among market participants, speculative bubbles, and herd behavior.

Chinn and Meese (1995) highlighted that, in the short term, models grounded in macroeconomic fundamentals fail to outperform a random walk in predicting exchange rates. Building upon these findings, Evans and Lyons (1999) assert that macroeconomic models fundamentally explain only a negligible proportion of exchange rate variation, necessitating the exploration of alternative approaches.

The introduction of the microstructure approach, as innovatively proposed by Evans and Lyons (1999), involves incorporating a variable that approximates the determinants of exchange rates. Significantly, they argue that "order flow" emerges as a key factor explaining a substantial portion of nominal exchange rate variation over a four-month period.

In the subsequent model presented by Evans and Lyons (2002), both microeconomic variables and microstructure determinants are integrated. Notably, the microstructure approach introduces a novel element where trading volume influences price movements, a departure from the macroeconomic approach where such an impact is absent.

Expanding on this, Evans and Lyons (2005a) introduce an exchange rate model based on microstructure theory, demonstrating superior out-of-sample forecasting performance compared to a random walk, especially within short to medium-term horizons ranging from one day to one month. Despite these promising short-term predictions, there remains a challenge in bridging the gap between short-term and long-term dynamics in the understanding of exchange rate behavior.

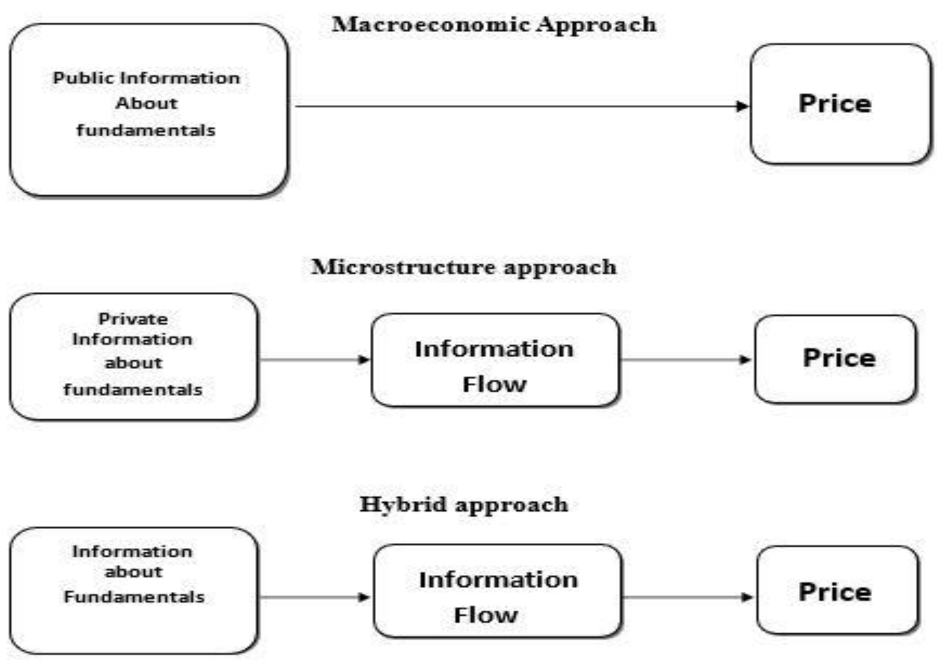
Within the microstructure approach, a pivotal element is the incorporation of crucial private information, which becomes aggregated through order flow dynamics. This signifies that information is gleaned and processed through the actual transactions occurring in the market.

An alternative perspective, known as the hybrid approach, emerges from the framework mentioned below. This methodology seeks a synthesis between the microstructure and other existing approaches. The term "hybrid" stems from the attempt to reconcile these two previously mentioned methods, clarifying that market participants derive their insights from both the ongoing order flow and publicly available announcements.

Essentially, the microstructure approach introduces a nuanced understanding of how private information influences order flow, while the hybrid approach attempts to strike a balance by acknowledging the significance of both private and publicly disclosed information in shaping market dynamics.

The Figure below illustrates the process of integrating information into prices according to the different theories of the foreign exchange market.

Figure 5:Process for integrating information into prices according to the different approaches



Source: Lyons (2001)

3. The Relationship Between Trading Volume and Market Returns

Numerous investigations have delved into the relationship between trading volume and market returns, offering diverse insights into this complex relationship. Authers such as Tauchen and Pitts (1983), Karpoff (1987), and Copeland (1976) have underscored the pivotal role played by trading volumes in shaping returns. Despite theoretical considerations posited by Epps (1976) and Jennings (1981) suggesting connections between volume, volatility, and returns, the predominant focus in this domain remains on empirical studies, as highlighted by Karpoff (1987).

Empirical examinations frequently note a positive correlation between trading volume and the absolute value of returns or return volatility, particularly evident in equity markets (Schwert, 1989; Gallant, 1992) and futures markets (Bessembinder and Seguin, 1993). In certain instances, the link between trading volumes and returns may exhibit positivity but with a less pronounced impact (Harris and Gurel, 1986; Karpoff, 1988).

Gallant (1992) accentuated the significance of incorporating trading volumes into studies exploring the relationship between return and volatility. Their findings revealed a negative relationship between returns and risk when volume was omitted, but this relationship turned positive upon the inclusion of volume in the analysis. Furthermore, the introduction of volume into volatility dynamics mitigated the impact of the leverage effect.

Bessembinder (1994) unearthed a negative correlation between expected volume and returns, whereas unexpected volume demonstrated a positive correlation. Hartman (1999) delved into the relationship between trading volume and price range in the forex market, examining how volume influenced different components of the price range.

Galati (2000) conducted research on interbank markets in emerging countries, uncovering a significant positive relationship between trading volume and exchange rate volatility, with exceptions noted in specific currencies. Lee and Rui (2000) emphasized the predictive relationship between trading volume and stock return volatility, indicating a bidirectional influence between the two. Llorente (2002) explored the impact of trading volume on stock returns, particularly underlining its significance on high-volume trading days.

Chen (2008) identified both linear and non-linear Granger causality relationships between trading volume and price, particularly in the Shanghai A share market. Gul and Javed (2009) discovered a robust positive correlation between various trading volume metrics and the performance of the Karachi Stock Exchange index. Pathirawasam (2011) identified a positive relationship between trading volume and portfolio returns, emphasizing the influence of past volume on current returns. Kamath (2008) established a causal relationship between Santiago Stock Exchange index returns and trading volume.

However, Remorov (2014) presented evidence of a negative relationship between trading volume and stock returns, especially during market crises. Gupta (2018) suggested that the strength of the relationship between trading volume and returns in Chinese and Indian markets depended on the investment time horizon. Sabri (2008) revealed a significant correlation between trading volume and the price movements of eight Arab markets. Chen (2008) disclosed a long-term causal relationship from price to trading volume for various shares. Glaser and Weber (2009) underscored the role of investor confidence and market returns in influencing trading volume.

Despite diverse findings, some studies, including Medeiros and Doornik (2008) and Akpansung and Gidigbi (2015), failed to establish a clear causal link between trading volume and returns. Bascl et al. (1996) suggested that stock prices alone could not entirely predict trading volume, raising questions about the Efficient Market Hypothesis. Akpansung and Gidigbi (2015) identified a long-term relationship between trading volume fluctuations and returns but couldn't determine the direction of this relationship. Miseman (2019) unveiled the predictive capabilities of trading volume in stock performance.

4. Volatility in FX market

Modeling exchange rate volatility has remained crucially important because of its diverse implications. Choo, Loo, and Ahmad (2002) explored the dynamics of exchange rate volatility, their analysis unveiled the persistence of volatility in the RM-sterling exchange rate. Across the sample analysis, GARCH models emerged as the most effective, with GARCH-in-mean models outperforming standard GARCH models for forecasting.

In their study, Dhamija and Bhalla (2010) emphasized the effectiveness of conditionally heteroscedastic models in modeling exchange rate volatility. The Integrated Generalized Autoregressive Conditional Heteroscedasticity (IGARCH) and Threshold Generalized Autoregressive Conditional Heteroscedasticity (TGARCH) models were identified as superior for forecasting the volatility of five daily currencies, namely the British pound, German mark, Japanese yen, Indian rupee, and Euro.

Clement and Samuel (2011) spotlighted the non-stationary nature of the exchange rate return series and the presence of asymmetry in the series residuals, urging further investigation into the impact of government policies on foreign exchange rates.

Further expanding the exploration of exchange rate volatility, Spulbar (2012) analyzed the impact of political and economic news from the euro area on the exchange rate between the Romanian currency and the Euro, employing GARCH models.

Additionally, Ramasamy and Munisamy (2012) reaffirmed the efficiency of GARCH models in predicting exchange rate volatility. Interestingly, they argued that the inclusion of EGARCH and GJR-GARCH models did not significantly enhance forecasting accuracy, underscoring the effectiveness of traditional GARCH models.

Çağlayan, Ün, and Dayıoğlu (2013) embarked on an examination of exchange rate volatility in different countries against the US dollar, employing monthly exchange rate data. Their research unveiled both asymmetrical and leveraging effects in these exchange rates when compared to the US dollar.

Furthermore, Bala and Asemota (2013) delved into the realm of exchange rate volatility using GARCH models. To make their analysis comprehensive, they considered various GARCH models, both with and without accounting for volatility breaks. What's particularly noteworthy in their findings is the concept of the leverage effect. This effect signifies an asymmetrical relationship between an asset's price movements and the volatility of its returns, in which price drops tend to result in more significant increases in volatility compared to price rises.

Surprisingly, the majority of the GARCH models they tested did not support the existence of a leverage effect. However, this perspective shifted when they introduced models with volatility breaks, indicating the importance of accounting for such breaks when assessing the presence of the leverage effect in exchange rate volatility.

Concurrently, Pelinescu (2014) conducted an examination of exchange rates concerning the Romanian leu and the euro, while accounting for the influence of various macroeconomic factors. The research, spanning daily data from 2000 to 2013, revealed that the exchange rates exhibited ARCH processes, establishing a correlation between exchange returns and volatility. These comprehensive studies collectively enrich the understanding of exchange rate volatility, shedding light on its multifaceted and context-specific nature.

Drawing parallels to these findings, Rofael and Hosni (2015) extended their inquiry into exchange rate volatility to Egypt, analyzing daily exchange rate data. Their findings uncovered periods of clustered volatility, indicating closely grouped high volatility phases. Moreover, they highlighted a potential risk stemming from the misalignment between exchange rates and the stock market, showcasing the intricate interplay of financial factors within the Egyptian context.

In addition, Ştefan (2015) focused on daily exchange rate volatility in the RON/EUR time series, utilizing GARCH models. The research pointed to the ARCH model as the best-fit, contributing valuable insights.

5. The relationship between trading volume and volatility

The relationship between trading volume and volatility has been extensively examined in equity markets by prominent studies like such as Andersen (1996) and Bollerslev and Jubinski (1999) these authors extensively delved into the link between trading volume and volatility in equity markets, while currency markets, despite their substantial scale, received less scrutiny until recent years. Ethier (1973) theorized that higher volatility might lead to reduced transaction volume, but this view clashed with conflicting perspectives on the impact of uncertainties on trading volume. Clark (1937) and Hooper and Kohlhagen (1978) suggested that risk-averse traders could negatively influence a country's international trade volume, citing factors like supply, demand, and volatility affecting traders' risk aversion.

Differing views emerged regarding the development of forward markets in the face of trader uncertainty. Viaene and de Vries (1992) proposed that varying perceptions among importers and exporters could heighten volatility, potentially influencing trading volume. Sercu (1992), in contrast, found that volatility could increase trading volume, explaining that in high volatility scenarios, prices might surpass trading costs, thus supporting international trade as per Sercu and Vanhulle (1992). However, the consensus on the relationship between volatility and international trade volume was not unanimous, as evidenced by the findings of Hagiwara and Herce (1999), who discovered a weak connection between trading volume and conditional volatility using a portfolio selection model for exchange rate determination.

Chang (2005) observed a positive correlation between daily yen/dollar futures volume and volatility, aligning with the Mixture of Distributions Hypothesis (MDH). This hypothesis posits an interconnected relationship between trading volume and volatility, anticipating that higher trading volume corresponds to increased volatility. This alignment with MDH was further supported by Bauwens (2006) in the context of the weekly Norwegian Krone/Euro exchange rate. Mougoué and Aggarwal (2011) extended this exploration to three foreign currency futures, finding resonance with the MDH.

Shahzad et al. (2018) expanded the scope to four exchange rates against the Dollar/British pound, Euro, Swiss franc, and Japanese yen finding results in line with the MDH. Finally, Sensoy and Serdengeçti (2019) investigated the US dollar/Turkish lira exchange rate, discovering a positive correlation between volatility and trading volume in this specific FX pair. These diverse findings collectively contribute to the evolving understanding of the complex relationship between trading volume and volatility in currency markets.

6. High frequency trading

The high frequency trading is an automated technique that uses complex algorithms and powerful computers to perform the transactions on the financial markets at a high speed. It can be used for numerous transactions, including the purchase and sale of shares, currencies, commodities and other financial assets.

these are the characteristics of high-frequency trading:

- Treating Numerous orders
- Quick withdrawal of orders
- Positions can be held for short periods
- Positions are closed at the end of the trading day
- Low margins per transaction

High frequency trading offers numerous advantages such as market liquidity and stability. It can also generate gains over long periods by enabling buyers and sellers to be quickly matched on the markets and finally lowering the market volatility.

However, examining HFT as an exchange mechanism implemented by various financial entities to bolster liquidity and allocate resources more effectively has raised pertinent questions. Analyzing the impacts of HFT reveals three main aspects: its effects on market liquidity, its influence on market integrity, and its potential systemic risks.

Market liquidity, a pivotal component in financial markets, depends on the ease with which investors can transact in substantial quantities at minimal cost, without adversely impacting prices. The microstructure of financial markets necessitates a liquid environment that allows for seamless trading, as defined by Harris and cited in Guyot (2007).

Delving into the realm of algorithmic and high-frequency trading, the theoretical landscape reveals varying perspectives. Brogaard (2010) reported positive effects of these trading strategies, particularly in the US market, where they bolster market liquidity. Linton (2011) uncovers the contribution of high-frequency trading to improved liquidity and reduced volatility in stock markets. Conversely, Hasbrouck and Saar (2012) shed light on how high-frequency trading during 2007-2008 led to narrower the price in some major stocks.

These studies underline a broader impact of high-frequency trading on market efficiency. Brogaard (2010) highlighted the rise in market efficiency due to improved liquidity and lower transaction costs facilitated by high-frequency trading. Chaboud et al. (2010) emphasize that high-frequency trading not only enhances market efficiency but also positively affects exchange rates without triggering increased market volatility.

Further studies emerge in the work of Hendershott and Riordan (2012), who reveal that high-frequency traders tend to consume liquidity when it is inexpensive and provide it when it is costly, playing a stabilizing role in the market.

Yet, not all research aligns with these positive outcomes. Hendershott and Moulton (2011) and Zhang (2011) introduce a counter-narrative, suggesting that high-frequency trading may increase market volatility in the US and result in an overreaction to earnings announcement by traders. This intricate tapestry of findings highlights the intricate nature of HFT's impact on financial markets, with diverse perspectives and outcomes.

Further insight is provided by Ekinci and Ersan (2018), who investigate HFT in the Istanbul stock market. They find that HFT is concentrated in high-market-capitalization stocks, suggesting a limited role across the market due to its technology-centric nature. Their findings refrain from providing a definitive judgment on whether HFT positively or negatively influences market quality.

Chancharat and Phuensane (2021) explore the role of high-frequency activity in the Thailand Stock Exchange from January 2016 to June 2018. Their research supports a negative relationship between high-frequency messages and the effective spread, implying that an increase in high-frequency activity tends to narrow the effective spread.

Building upon this, Ekinci and Ersan (2022) discovered a negative impact of high-frequency activity on market quality, despite its relatively minor presence. They highlight a reduction in liquidity provision by non-HFT traders as high-frequency trading intensifies.

Contrarily, Ekinci and Ersan (2022) assert that the growth of algorithmic trading substantially boosts market liquidity and volatility, especially in the context of large-cap stocks, with no significant impact on the price. These diverse findings underscore the complex nature of HFT's implications for market microstructure.

7. Conclusion

In summary, this chapter has surveyed a broad spectrum of studies and contemporary research outcomes, emphasizing the substantial impact of the microstructure approach on the forex market. Across its sections, key findings have been outlined, fundamentally altering the perspectives of market participants regarding the complexities of foreign exchange dynamics. This chapter underscores the indispensable significance of the microstructure approach in comprehending and interpreting movements within the forex market. Furthermore, it accentuates the pivotal role played by high-frequency trading volume and its consequential influence on shaping price movements..

EMPIRICAL PART

Chapter 4: Methodology: GARCH models

1. Introduction

The Autoregressive Conditionally Heteroskedasticity (ARCH) model, introduced and developed by Engle (1982), has been widely used in modeling financial series. Bollerslev (1986) generated these models (Generalized ARCH) and brought greater versatility and efficiency to modeling by considering past conditional variance. Their characterization is based on the notion of conditional past variance.

The GARCH model is characterized by the volatility specified as a linear function of the squares of past innovations. By construction, the conditional variance depends solely on modeling past returns, and therefore has the same effect on volatility.

Numerous extensions have been made to this model extensions were made to this model, notably asymmetrical extensions, since this model was contradicted a large number of studies showing that financial series have a leverage effect, as shown by Black (1976).

Among these extensions, we find the Asymmetric GARCH model (AGARCH or TGARCH) introduced by Rabemananjara and Zakoïan (1993). Following that, Pan (2008) proposed the Power ARCH (APGARCH) model, which encompasses a large number of GARCH-type models.

After ensuring identifiability and stationarity, the crucial step is the estimation of the unknown coefficients of the model. Following that, a validation procedure is necessary to confirm the choice of the p and q orders of the model.

This chapter serves as an introduction to standard GARCH (Generalized Autoregressive Conditional Heteroskedasticity) models, explaining the essential conditions for stationarity, the process of estimation, and the asymptotic properties of the estimator. Furthermore, it explores diverse GARCH models, including EGARCH (Exponential GARCH), TGARCH (Threshold GARCH), and GJR GARCH models, outlining their unique characteristics, benefits, and highlighting distinctions from the standard GARCH model.

2. Modelling volatility

To address the shortcomings of ARMA (p, q) representations for monetary and financial problems, Engle (1982) proposed a new class of conditionally heteroskedastic autoregressive models (ARCH) capable of capturing volatility behavior over time.

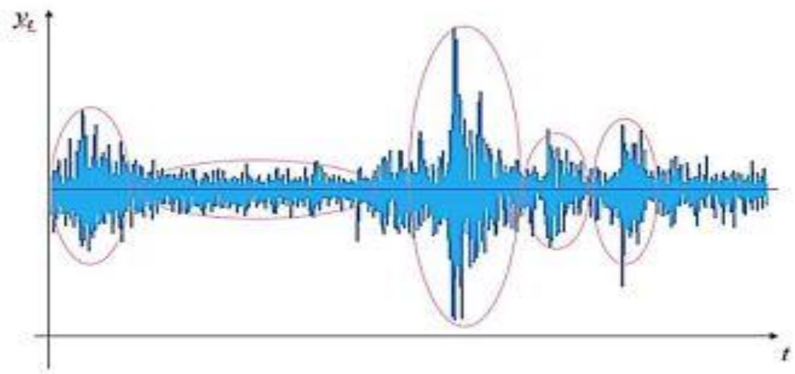
Engle (1982) proposed these processes to address the shortcomings of the ARMA class of models, especially concerning financial time series that exhibit time-varying volatility (or instantaneous variability measured by conditional variance) and asymmetric adjustments.

The model consists of two equations. The first relates returns to certain explanatory variables, while the second models the conditional variance of the residuals. Engle's proposed principle involves introducing dynamics into the determination of volatility by assuming that the variance is conditional on the information available to us.

2.1. ARCH models

ARCH models are commonly used to characterize financial time series volatilities, often characterized intensively agitated periods followed by periods of relative calm.

Figure 6:Illustration of conditional autoregressive heteroscedasticity



Source: Bollerslev,1986

We can see that there are periods when returns are much more volatile than at other times. More precisely, we observe a "cluster" behavior of returns (periods of high and low volatility). The assumption of constant volatility is called into question.

In the case of time-varying volatility, we speak of "heteroscedasticity", and conversely, in the case of constant volatility over time, we speak of "homoscedasticity".

2.1.1. The Arch process

Determining the distribution of ε_t conditionally on all past values X_{t-1}, X_{t-2} ... Let's assume that we have...

$$X_t = \varepsilon_t$$

The distribution of t conditional on the past is as follows:

$$\varepsilon_t | X_{t-1}, X_{t-2} \ldots \sim N(0, \sigma_t^2)$$

Where the conditional variance σ_t^2 depends on time and is equal to

$$\sigma_t^2 = Var(\varepsilon_t | \varepsilon_{t-1}, \varepsilon_{t-2}, \ldots) = \alpha_0 + \alpha_1 X_{t-1}^2 + \cdots + \alpha_p X_{t-p}^2$$

The model for X_t that we have just defined corresponds to the ARCH(p) process. Thus, σ_t^2 is linearly related to the square of the last p observations. If the observations have high absolute values, σ_t^2 tends to be high as well, whereas small observations result in lower volatility. Similar to the parameters of ARMA models, the parameters of ARCH models can be estimated using maximum likelihood estimation, the method of generalized moments, or the quasi-maximum likelihood method.

2.1.2. Properties of ARCH process

If (X_t) is an ARCH(p) process, then:

- $E(X_t | X_{t-1}, \ldots, X_0) = 0$
- $E(X_t) = 0$
- $Var(X_t | X_{t-1}, \ldots, X_0) = \alpha_0 + \alpha_1 X_{t-1}^2 + \cdots + \alpha_p X_{t-p}^2$
- $Var(X_t) = \frac{\alpha_0}{1-\alpha_0+\cdots,+\alpha_p} si \sum_{i=1}^{p} \alpha_i < 1$

Thus, unlike the unconditional variance, the conditional variance is not constant over time (t).

2.2.GARCH models

The ARCH model falls short in efficiently capturing features associated with the volatility of an extensive dataset from the past. Notably, as the number of past innovations considered in the model increases, so does the number of parameters. In practical terms, an ARCH model exhibits similarities to a moving average. To address these limitations, Bollerslev (1986) introduced the GARCH model (Generalized Autoregressive Conditional Heteroskedasticity). Unlike the ARCH model, the GARCH model not only takes into account past innovations but also considers previous conditional variances. This enhancement enables the GARCH model to capture a wealth of information regarding volatility.

One advantage of GARCH models lies in their ability to flexibly model changing volatility over time. By incorporating both past innovations and conditional variances, GARCH models can more effectively adapt to evolving patterns in volatility, providing a nuanced understanding of how volatility fluctuates in response to changing market conditions. This adaptability is particularly valuable when dealing with financial time series data, where volatility can exhibit dynamic and nonlinear behavior.

Additionally, GARCH models are known for their ability to capture volatility clustering, a phenomenon where periods of high volatility tend to cluster together. This feature is crucial for understanding financial markets, as it acknowledges that volatility is not uniformly distributed over time but rather tends to exhibit clustering patterns. GARCH models, with their consideration of past conditional variances, excel in capturing and explaining these clustering tendencies in volatility.

According to Bera and Higgins (1993), indicates that the GARCH(1,1) model offers a versatile and economical representation of conditional variance dynamics. It proves adept at capturing the complexities inherent in the majority of financial series. The GARCH(1,1) model is expressed as follows:

$$Y_t = \mu + \varepsilon_t, avec\ \varepsilon_t = \sigma_t . z_t; z_t \sim N(0,1)$$

The equation for the conditional variance of the residuals is defined as: β_1

$$\sigma_t^2 = \alpha_0 + \alpha_1 . \varepsilon_{t-1}^2 + \beta_1 . \sigma_{t-1}^2 (1)$$

Where $\alpha_0 > 0$, $\alpha_1 \geq 0$, and $\beta_1 \geq 0$ are constants

The ARCH(1) model corresponds to $\beta_1 = 0$.

The constraint $\alpha_1 + \beta_1 < 1$ implies that the unconditional variance of the return series ε is finite, and the conditional variance σ_t^2 evolves over time.

It also provides the necessary and sufficient condition for the stochastic process $\sigma_t^2; t \in Z$ to be a unique strictly stationary process with $E(\sigma_t^2) < \infty$.

Two key properties can be noted from equation (1). Firstly, a high value of ε^2 or σ^2results in a high value of σ^2, generating volatility clustering commonly observed in time series data. Secondly, the tail distribution is thicker than that of a normal distribution.

2.2.1. Properties of GARCH process

Similarly to ARCH process, in the case of GARCH processes;

$$E(X_t | X_{t-1}, \dots, X_0) = E(\varepsilon_t | X_{t-1}, \dots, X_0) = E(\varepsilon_t) = 0$$

$$E(X_t) = E\big(E(X_t | X_{t-1}, \dots, X_0)\big) = 0$$

2.2.2. GAECH models

- TGARCH (The Threshold GARCH)

The Threshold GARCH (T-GARCH) model is an extension of the traditional GARCH model that introduces a threshold parameter. This threshold allows the model to account for regime changes in volatility, where the response of volatility to shocks may differ based on certain conditions being met.

Unlike standard GARCH models, which assume a constant response to shocks, T-GARCH models recognize that market dynamics can vary under different circumstances. The introduction of a threshold parameter enables the model to capture shifts in volatility regimes, making it particularly useful for analyzing financial time series data characterized by changing market conditions.

In essence, the T-GARCH model offers an enhanced ability to capture non-linearities in volatility, responding to the recognition that financial markets may exhibit distinct behaviors in different states or regimes. This additional layer of complexity makes T-GARCH models valuable for addressing situations where the impact of shocks on volatility is contingent on specific conditions being met.

- E-GARCH (Exponential GARCH)

Despite being widely used, ARCH and GARCH models possess several limitations. Nelson (1991) particularly criticized GARCH models on three grounds: firstly, the constraint of parameters to be positive at all times; secondly, the absence of consideration for the asymmetry effect, also known as the leverage effect; and thirdly, the difficulty in measuring the persistence of shocks on volatility. To address these shortcomings, Nelson (1991) introduced the Exponential GARCH (EGARCH) model, which presents improvements over the standard GARCH model.

The Exponential GARCH (EGARCH) model presents notable advantages when compared to its GARCH counterpart. Firstly, it introduces greater flexibility by removing the constraint that parameters must be strictly positive, allowing for a more nuanced representation of various facets of volatility. Secondly, the EGARCH model inherently addresses the asymmetry effect, recognizing that volatility reacts dissimilarly to positive and negative shocks. This feature enhances its ability to capture the complexities of market dynamics. Lastly, the EGARCH model offers a more direct and interpretable measure of the persistence of shocks on volatility in comparison to the GARCH model. This characteristic contributes to a clearer understanding of the prolonged impact of shocks on volatility patterns, providing valuable insights for risk assessment and financial decision-making.

The primary divergence between the Exponential GARCH (EGARCH) and GARCH models centers on their treatment of asymmetry in volatility responses to shocks. In the conventional GARCH model, there is an implicit assumption of symmetric responses to positive and negative shocks, implying that the influence on volatility is uniform regardless of the direction of the shock.

In contrast, the EGARCH model introduces a higher degree of flexibility by allowing for asymmetric responses. This acknowledges the possibility that the impact of positive and negative shocks on volatility may vary. This enhanced flexibility is particularly valuable in capturing the intricate dynamics inherent in financial time series data, where asymmetry in volatility responses is a common observation.

By recognizing and accommodating asymmetry, the EGARCH model provides a more realistic representation of how financial markets react to different shocks. Investors and market participants often respond differently to positive and negative news, and this behavioral nuance is reflected in the observed patterns of volatility.

The first-order EGARCH process (or EGARCH(1,1)) specifies the model as follows;

$$Y_t = \mu + \varepsilon_t, avec\ \varepsilon_t = \sigma_t . z_t ; z_t \sim N(0,1)$$

The equation for the conditional variance of the residuals is defined as follows;

$$\log(\sigma_t^2) = \alpha_0 + \alpha_1 . g(\varepsilon_{t-1}) + \beta_1 . \log \sigma_{t-1}^2$$

Where $\varepsilon_1$follows a normal distribution and is a weak white noise, and the function $g(\varepsilon_{t-1})$ is satisfied.

$$g(\varepsilon_{t-1}) = \alpha . \varepsilon_{t-1} + \gamma(|\varepsilon_{t-1}| - E(|\varepsilon_{t-1}|))$$

The coefficient γ represents the leverage effect of shocks on volatility. The main advantage of the EGARCH model is that it is not necessary to impose positive restrictions on the variance coefficients. The coefficients γ should be negative to highlight asymmetric effects.

- GJR-GARCH (Glosten, Jagannathan, and Runkle GARCH)

Within the symmetric GARCH model, both positive and negative shocks are assumed to exert an equal impact on conditional variance. However, empirical observations in stock price behavior reveal an asymmetry, where negative surprises tend to induce a more substantial increase in volatility compared to positive surprises. In response to this asymmetry, GARCH models have been adapted to consider the effects of positive and negative shocks differentially. Notably, models like the GJR (Glosten, Jagannathan, and Runkle) and the Exponential GARCH, introduced by Nelson in 1991, incorporate this asymmetry explicitly. These models aim to capture the nuanced response of volatility to different shock scenarios, recognizing the inherent asymmetry observed in financial markets.

The GJR (1,1) model is specified as follows

$$Y_t = \mu + \varepsilon_t, avec\ \varepsilon_t = \sigma_t . z_t ; z_t \sim N(0,1)$$

The equation for the conditional variance of the residuals is defined as follows:

$$\sigma_t^2 = \alpha_0 + \alpha_1 . \varepsilon_{t-1}^2 + \gamma . \left(I_{\varepsilon_{t-1<0} \varepsilon_{t-1}^2} \right) + \beta_1 . \varepsilon_{t-1}^2$$

Where Z_t represents a weak white noise with zero mean and constant variance over time, and the coefficients α_1, β_1, and γ are real parameters. $I_{\varepsilon_{t-1<0}}$ denotes the indicator function such that

$$I_{\varepsilon_{t-1<0}} = \begin{cases} 1 & si\ \varepsilon_{t-1} < 0 \\ 0 & sinon \end{cases}$$

The structure of this model implies that a positive ε_t contributes to $\alpha_1 .\ \varepsilon_{t-1}$ to σ_t^2, while a negative ε_t has a more significant impact of (α_1+ γ). ε_{13} with $\gamma > 0$. This means that if the γ parameters are significantly positive, negative innovations would induce greater volatility than positive innovations of the same magnitude.

The distinctive feature of this model is its recognition that a negative shock has a more substantial impact than a positive shock, capturing what is known as the leverage effect. Similar to the GARCH model, the GJR-GARCH model effectively captures volatility clustering. Moreover, it is demonstrated that the unconditional distribution displays excess kurtosis even under the assumption of a Gaussian distribution.

Considering long-term effects, the FIGARCH (Fractionally Integrated Generalized Autoregressive Conditional Heteroskedasticity) and FIEGARCH (Fractionally Integrated Exponential Generalized Autoregressive Conditional Heteroskedasticity) models come into play. These models allow for the incorporation of information asymmetry, wherein agents exhibit different behaviors based on whether the variable being explained is rising or falling. This behavior is evident in stock prices, where negative errors lead to a more rapid decline than positive errors, explaining the phenomenon of stock prices dropping significantly before rebounding.

3. Conclusion

Volatility plays a crucial role in financial decision-making, and several key characteristics of volatility have been identified in financial markets. These include the presence of fat-tailed distributions, volatility clustering, and the leverage effect. In this chapter, we explored various GARCH models, shedding light on their pivotal role in understanding and modeling exchange rate return volatility. These models offer a robust framework for accommodating the inherent heteroskedasticity in financial data, enabling us to capture the dynamic nature of volatility over time. Their versatility, precision, and ability to distinguish between short and long-term patterns make them indispensable tools for risk management and informed decision-making in the realm of foreign exchange.

Chapter 5: Data and Empirical results

1. Introduction

This chapter initiates a comprehensive exploration of the connections among trading volume, volatility, and exchange rate returns, emphasizing the microstructure of foreign exchange markets. Initially, it closely analyzes the dynamics of exchange rate returns, particularly focusing on the USD/TND and EUR/TND pairs. Following this, a detailed examination of descriptive statistics for these rates and their corresponding trading volumes is conducted. Afterwards, preliminary tests are carried out to comprehend the underlying mechanisms driving the studied series. Finally, the chapter investigates the influence of trading volume and volatility on exchange rate returns. The initial phase concentrates on evaluating the impact of trading volume on exchange rate returns, followed by an exploration of the relationship between volume and volatility. This study aims to better understand how trading volume influences price changes within the foreign exchange market, leveraging insights from the market's microstructure while acknowledging its inherent inefficiencies and disparities in access to information among participants..

2. Data Description

As we try to seek for the trading volume and volatility effect on the exchange rates dynamics, we consider a sample collected from the major electronic trading platforms in the foreign exchange markets; Refinitiv platform which provides the entire market information and updated news. We will focus on series of exchange rates EUR/TND and USD/TND, as well as their respective trading volumes. The empirical study will primarily examine the daily data of the exchange rates and the trading volumes. This will potentially allow us to refine our study and offer a new perspective on the exchange rate dynamics in the Tunisian interbank market.

The sample covers the period from 31/01/2019 to 31/04/2023 giving almost a total of 1226 observations.

Table 2 provides a detail account of the different variables that are adopted. It lists also the source for each variable.

Table 2: Data description

Variables	Description	Measure	Source
Endogenous variable	Exchange rates returns (EUR/TND & USD/TND)	Rt = Log (Pt/Pt−1)	Datastream "Refinitiv"
Explanatory variable	Trading volume of each exchange rate	Vt= trading volume	Datastream "Refinitiv"

3. Preliminary tests

3.1. Descriptive statistics

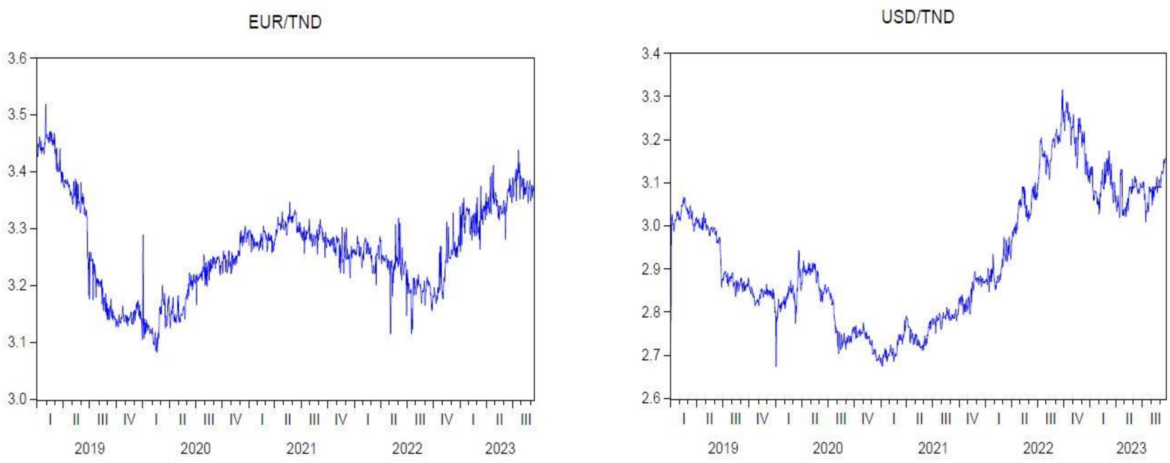


Figure 7:The exchange rates

Figure 7 shows the exchange rates evolution. It is clear that the exchange rates, having their ups and downs, fluctuate over the years.

In 2019, the Tunisian dinar experienced a positive trend after a period of depreciation. This improvement has been attributed to several key factors. Firstly, there was a significant increase in foreign currency liquidity on the foreign exchange market, meaning that more foreign currency was available for transactions. This increased liquidity helped stabilize exchange rates and prevent further depreciation of the dinar.

In addition, the reference to stabilizing the trade deficit is important. The trade deficit is the difference between a country's exports and imports. Stabilizing this deficit means that Tunisia has managed to better balance its international trade, which can have a positive impact on the value of the dinar. When a country imports much more than it exports, this can lead to increased demand for foreign currency, which can exert downward pressure on the value of its currency. Stabilizing the trade deficit can help reduce this pressure.

Foreign currency receipts from tourism also increased, boosting the country's foreign exchange reserves. Finally, the easing of concerns and negative expectations on the part of economic players boosted confidence in the economy, encouraging investment and promoting Tunisia's overall monetary stability.

In 2020, Tunisia faced an economically challenging year, marked by negative economic growth, high unemployment and growing poverty. Despite these challenges, the appreciation policy of the central bank ran counter to expectations that the dinar should have depreciated to reflect the difficult economic situation and rebalance the trade balance. This appreciation had two major consequences: it favored imports and penalized exports. It also contributed to a deterioration in the level of foreign indebtedness, as the trade deficit - the main component of the current account deficit - had to be covered by foreign currency, mainly from external credits.

Overall, the Tunisian dinar experienced significant fluctuations on the foreign exchange market. It appreciated by 1.3% against the euro, meaning that the national currency strengthened against the European currency over the year. However, against the US dollar, the dinar depreciated by 6.3%. This divergence is largely explained by the evolution of the US dollar on the international scene, where it has gained in strength against the euro.

In 2021, the US dollar enjoyed a period of relative strength against many other currencies, including the euro. This is due in part to the economic recovery in the United States, higher interest rates and the Federal Reserve's monetary policy. When the US dollar appreciates against the euro, the Tunisian dinar, which is often linked to the dollar, can also lose value against the euro.

In 2022, there was a marked depreciation of the Tunisian dinar against the US dollar. This depreciation was particularly marked between March and November. However, from November onwards, the dinar began to stabilize, thanks in part to the depreciation of the US dollar on the international foreign exchange markets. Overall, over the full year 2022, the Tunisian dinar depreciated by an average of 9.9% against the US dollar. By contrast, it appreciated by 1.1% against the euro. This appreciation against the euro can be explained by various factors, including movements on international markets and monetary policies.

The fluctuation of the euro against the dollar has led to a convergence of the Tunisian dinar against both currencies. An appreciation of the dollar against the dinar has various consequences: an increase in the import bill in dollars, a rise in the public debt denominated in U.S. currency, a higher cost of servicing the debt in dollars, a weakening of the purchasing power of Tunisians, an increase in the production costs of Tunisian companies, and, if applicable, an increase in the state's compensation expenses.

On the other hand, Tunisian exports invoiced in dollars would become more competitive, and our dollar reserves would be revalued. Furthermore, a significant decrease in the euro against the dinar (which is not yet the case) would reduce import costs denominated in euros and ease the burden of the public debt, especially since it is predominantly denominated in euros. However, this could also decrease revenues from exports to the Eurozone, converting into fewer dinars, and devalue euro reserves. In any case, a potential economic crisis in Europe coupled with sustained inflation would impact European demand for goods and services offered by Tunisia, a detrimental scenario for the Tunisian economy.

According to the economist Moez Hddidane « If Europe aims to achieve complete energy independence by 2035, Tunisia must also diversify its foreign trade in favor of new markets ».

Moreover, the Tunisian Dinar is included in a currency basket. This basket consists of multiple currencies, but the Euro and the United States Dollar carry the most significant weight or importance within this basket. This means that changes in the exchange rate EUR/USD, have a substantial impact on the overall value of this currency basket.

To elaborate further, when the EUR/USD exchange rate fluctuates, it directly influences the composition and value of the currency basket in which the Tunisian Dinar is a part. As a result, fluctuations in the EUR/USD exchange rate can significantly affect the value of the Tunisian Dinar. These changes, in turn, affect the Tunisian Dinar's exchange rates with other currencies and its overall performance in international financial markets.

Therefore, by closely monitoring and analyzing movements in the EUR/USD exchange rate, one can gain valuable insights into how the Tunisian Dinar is likely to perform and how it may be impacted by shifts in the global currency market. This is why the evolution of the EUR/USD exchange rate is a critical factor in understanding the dynamics of the Tunisian Dinar's exchange rate and its position in international trade and finance.

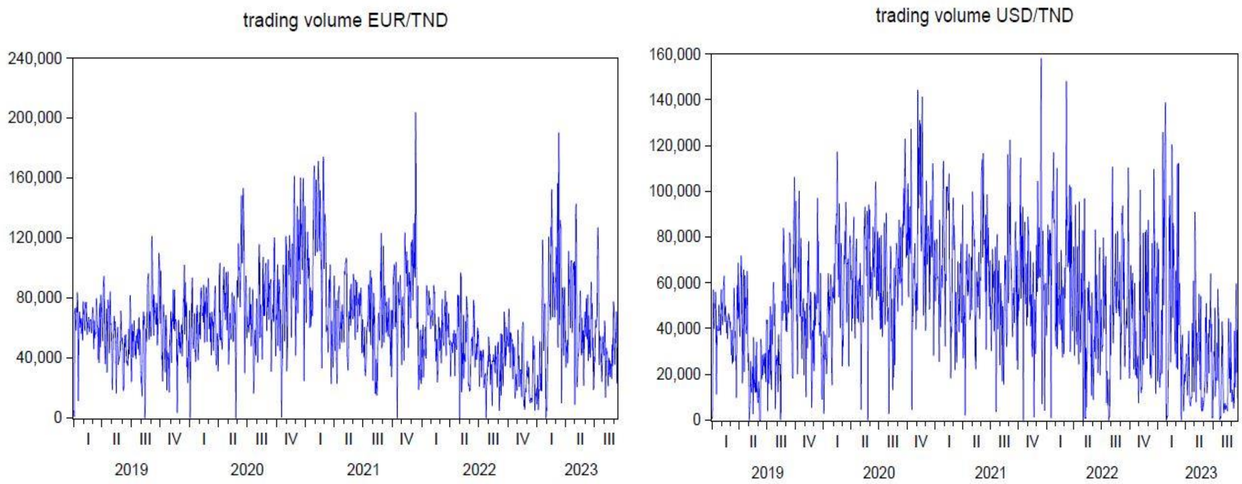


Figure 8:The trading volume

In these two graphs, we can see a representation of the trading volume for the period under study. We notice that the trading volume fluctuates around an average of 63,664 thousand euros for the EUR/TND volume and 51,319 thousand dollars for the USD/TND trading volume.

We present the descriptive statistics of the main variables in this study, which include the exchange rate (EUR/TND), the exchange rate (USD/TND), and their respective trading volumes.

Table 3 : Descriptive Statistics

	Exchange rate		**Trading volume**	
	EUR/TND	USD/TND	EUR/TND	USD/TND
Mean	3.261	2.925	63664	51319
Median	3.259	2.879	60973	50131
Maximum	3.518	3.315	203561	158004
Minimum	3.082	2.673	3.1414	9
Std. Deviation	0.082	0.154	30120.68	27577.9
Skewness	0.0244	0.362	0.748	0.353
Kurtosis	2.608	2.028	4.263	3.019
Observations	1226	1232	1226	1232

Source: My own estimations based on Eviews software

It is clear from the table that the difference between the maximum and minimum values indicates a significant dispersion in the trading volume.

The standard deviations, which measures the fluctuations of the variables around their means, are more or less small, the highest standard deviation is viewed for the trading volume of each exchange rate, the high values taken by the standard deviation could be interpreted by the high market volatility during the period studied.

It stands out from Table that the Kurtosis is higher than three only for the trading volume. In other words, while most the exchange rates are platykurtic, the trading volume is characterized by thick tails because they are leptokurtic.

The Skewness coefficient is statistically different from zero for all the considered variables. It bears a positive sign for all the considered variables. In this way, we can conclude that all the distributions are found asymmetric. the series of each variable are right skewed.

As we can remark, the Kurtosis and Skewness coefficients are different from those characterizing the normal distribution. Intuitively, we may claim that the considered distributions are not normal. We run the Jaque-Bera test to make sure of the non-normality of the distributions.

3.2. Normality Test

The Jarque-Bera test is a hypothesis test that seeks to determine whether data follows a normal distribution.

As with any hypothesis test, you need to establish a null hypothesis to be tested:

H_0: The data follows a normal distribution.

H_1: The data does not follow a normal distribution.

Table 4: Normality test

	Exchange rate		**Trading volume**	
	EUR/TND	USD/TND	EUR/TND	USD/TND
Jarque-Bera	17.397	75.448	196.014	25.668
Probability	0.000	0.000	0.000	0.000

Source: My own estimations based on Eviews software

These findings are confirmed by the Jarque-Bera test, rejecting the null hypothesis of normality for all the considered variables (P-value<0.05).

3.3. Stationarity test

From the figure depicting the evolution of exchange rate returns, it is evident that the series is not stationary. Therefore, we will calculate the returns. In the following, we define the return (Rt) of the exchange rate as follows:

$$Rt = \text{Log}\ (Pt/Pt-1)$$

Where Pt denotes the exchange rates

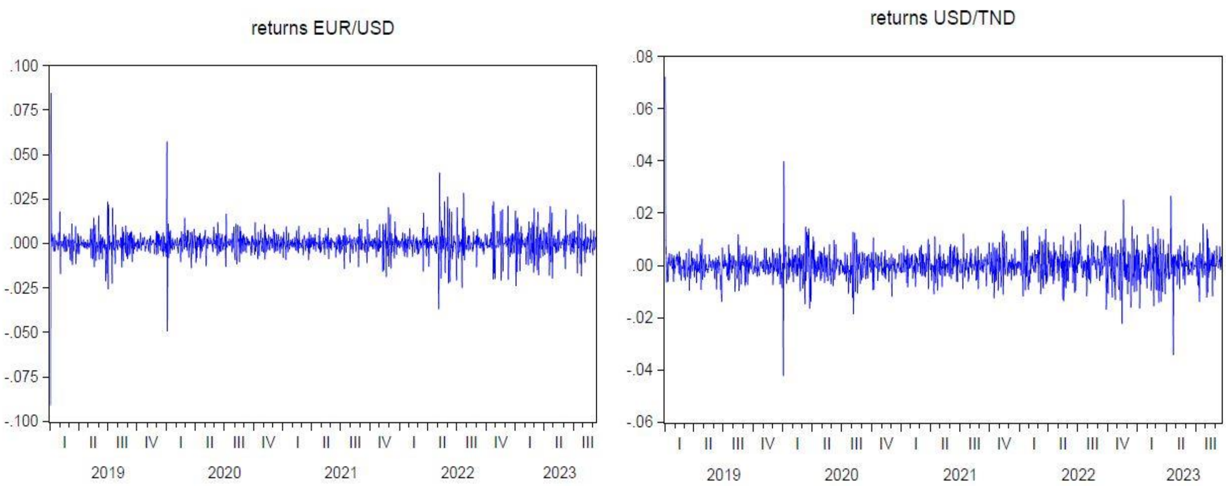


Figure 9: The exchange rates returns

The visualization of the figure above, depicting the return trends of the two studied exchange rates, may potentially help verify the stationarity of the return series

Graphically, it appears that both series are stationary, and the fluctuations are quite pronounced. However, it is important to rely on unit root tests again to verify stationarity.

In order to test the stationarity, we will apply the Augmented Dickey-Fuller test to the studied exchange rates. The Augmented Dickey-Fuller tests are used to determine whether a time series is stationary or non-stationary by identifying a deterministic or stochastic trend.

The ADF test is the most commonly used due to its simplicity, and it helps detect the presence of a unit root and determine the appropriate way to stationarize the series under study. This test has been subject to some criticism, leading to the development of the Phillips-Perron tests (1988), which are an extension of the Dickey-Fuller test.

The simple Dickey-Fuller test (1979) is a unit root test (or non-stationarity test) with the null hypothesis of non-stationarity for a first-order autoregressive process. Consider a process (Xn) satisfying the following AR (1) representation:

$$X_n = \rho X_{n-1} + u_t$$

where u_t is white noise, and $\rho \in$ R.

The general principle of the Dickey-Fuller test is to test the null hypothesis of the presence of a unit root:

$$H_0 : \rho = 1$$

$$H_1 : |\rho| < 1$$

- If ρ = 1, then the variable X_n is an integrated order 1 variable. This is the case for a random walk model without drift. If ρ < 1, then the variable X_n is stationary.
- If ρ = 1, the variance of X_n depends on n, which contradicts the stationarity condition. However, if ρ < 1, the variance of X_n is independent of n (constant). The statistic for this test is the usual test statistic with critical values calculated by Dickey and Fuller.

Table 5: Results of the panel unit root tests

	EUR/TND		**USD/TND**	
	Trend and constant	constant	Trend and constant	constant
Rt	-31.00771 (-3.413493)	-30.98010 (-2.863697)	-31.53108 (-3.413472)	-31.50205 (-2.863683)
Vt	-4.902885 (-3.413518)	-4.792831 (-2.863712)	-5.548709 (-3.413493)	-5.448177 (-2.863697)

Source: My own estimations based on Eviews software

We note that the values within parentheses are critical values for the 5% confidence level.

Based on this table, it is evident that the null hypothesis of the existence of a unit root for all four series in this study is rejected at the 5% confidence level. Therefore, the return series and the trading volume series are indeed stationary, which is also confirmed graphically as shown earlier.

4. The Generating Process of Exchange Rate Returns in the Tunisian Foreign Exchange Market

In the following section, we will identify the specific generative processes for the exchange rate returns and the trading volume series using the Box and Jenkins methodology. Finally, we will model conditional variance using the univariate ARCH test.

4.1. Modeling the conditional expectation of returns

Modeling the conditional expectation of returns will enable us to define the ARMA (p, q) process that generates the series of the exchange rates returns studied. The autoregressive (AR) part is a linear combination of the past values of the process. The moving-average part (MA) is a linear combination of the past values of a white noise.

The ARMA (p, q) process is identified in three stages:

- Identification of the process and determination of the orders p and q.
- Estimation of model coefficients.
- Analysis of coefficients and residuals.

4.1.1. Identification of the process

To begin with, one must initiate the process of determining the lag parameters for the AR (AutoRegressive) and MA (Moving Average) processes. For the sake of parsimony, there are two potential options: either an AutoRegressive process AR(p) or a Moving Average process MA(q). In this section, we will rely upon the autocorrelation function plot of the exchange rate returns series.

- The Autocorrelation Function (ACF)

  Serves to identify the order of a Moving Average (MA) process. The order of the process corresponds to the value of "q," where autocorrelations become insignificant beyond order q+1. Based on the correlogram (Annex1), it is observed that autocorrelations become insignificant starting from order 2 for USD/TND and order 3 for EUR/TND. According to the correlogram, the order of the MA process for USD/TND is 1, and for EUR/TND, it is 2.

- Partial Autocorrelation Function (PACF)

  Following a similar logic to that of a Moving Average (MA) process, partial autocorrelations become insignificant beyond order p+1, aiding in determining the lag of an AutoRegressive (AR) process. As significant partial autocorrelations are observed, it can be noted that they become insignificant starting from order 2 for USD/TND. Therefore, it corresponds to an AR (1) process. For EUR/TND, it appears to be an AR (3) process, as the significant partial autocorrelations vanish starting from order 3.

In this step, we will proceed with the estimation of the various processes using the least squares method. The estimation results for the different models of daily exchange rate returns are presented in the following table:

Table 6:USD/TND returns process

	Significance of all parameters	**R-squared**	**Log likelihood**	**Schwarz Criterion**	**Akaike info Criterion**
AR(1)	significant	0. 360299	-1072.486	1.669872	1.650206
MA(1)	significant	0. 470015	-1065.505	1.650803	1.627195
ARMA(1,1)	**significant**	**0.482963**	**-1035.270**	**1.570467**	**1.566546**

Source: My own estimations based on Eviews software

The ARMA(1,1) process exhibits the highest R^2 and log-likelihood values among those examined, thus yielding the lowest Akaike Information Criterion and Schwarz Criterion.

Table 7:EUR/TND returns process

	Significance of all parameters.	**R-squared**	**Log likelihood**	**Schwarz Criterion**	**Akaike info Criterion**
AR(1)	significant	0.466802	-1296.069	2.047669	2.031947
AR(2)	significant	0.468994	-1285.272	2.007939	1.988273
AR(3)	Not significant	****	****	****	****
MA(1)	**significant**	**0.494449**	**-1243.730**	**1.885599**	**1.881678**
MA(2)	significant	0.470374	-1275.996	2.000827	1.977214
ARMA(1,1)	Not significant	****	****	****	****
ARMA(2,1)	Not significant	****	****	****	****
ARMA(3,1)	Not significant	****	****	****	****
ARMA(1,2)	significant	****	****	****	****
ARMA(2,2)	significant	****	****	****	****
ARMA(3,2)	Not significant	****	****	****	****

Source: My own estimations based on Eviews software

**** A model featuring non-significant parameters

After estimating the parameters, we examine the estimation results:

Firstly, the coefficients of the models should be significantly different from 0, and the Student's t-test is applied conventionally.

MA(1) process exhibits the highest R^2 and log-likelihood values among those examined, thus yielding the lowest Akaike Information Criterion and Schwarz Criterion.

4.1.2. Autocorrelation test

Secondly, the residuals should exhibit characteristics of white noise. The Box-Pierce Q-statistic is used to test this hypothesis. The Box-Pierce Q-statistics for various exchange rates should be compared to critical values obtained from a chi-squared distribution with degrees of freedom equal to (q-1). In the following, a lag of 20 is arbitrarily chosen. The results below were obtained from the correlograms of the residuals, with (χ^2 (20-1=19) = 30.14).

$$Q\ (USD/TND) = 16.106 < 30.14 = \chi^2(19)$$

$$Q\ (EUR/TND) = 17.348 < 30.14 = \chi^2(19)$$

These results indicate that the Box-Pierce Q-statistics for both USD/TND and EUR/TND are less than the critical value of 30.14 for a chi-squared distribution with 19 degrees of freedom ($\chi^2(19)$). This suggests that the residuals for both exchange rates exhibit characteristics consistent with white noise, supporting the validity of the model.

4.1.3. Heteroskedasticity test

The series of returns are characterized by alternating periods of high volatility followed by periods of low volatility, which is similar to an ARCH effect. It is thus possible to make a dynamic forecast of the chronicle in terms of mean and variance. To detect this possible ARCH effect, we will use the correlogram of the squared residuals to verify the presence of autocorrelation of the squared residuals of the models already estimated from the conditional means.

The LM (Lagrange Multiplier) test for ARCH (Autoregressive Conditional Heteroskedasticity) assesses the presence of conditional heteroskedasticity in a time series dataset. Specifically, it examines whether the squared residuals from a statistical model exhibit significant autocorrelation, indicating the presence of ARCH effects. The test involves comparing the fit of a model with squared residuals against a model without squared residuals. A rejection of the null hypothesis suggests the existence of ARCH effects, implying that the volatility of the time series is not constant over time.

The use of the Lagrange Multiplier (LM) test results in the rejection of the null hypothesis of "no ARCH effects" at a 5% significance level.

Table 8:ARCH-LM test

Exchange rate returns	EUR/USD	USD/TND
ARCH-LM statistic test	246.1831	90.89138
P-value	0.00000	0.00000

Source: My own estimations based on Eviews software

The results from the LM test suggest a notable presence of the ARCH effect, indicating pronounced volatility patterns in the return series. As a consequence, the application of GARCH models emerges as a viable approach for effectively modeling the data within the return series.

The purpose of this approach is to determine the generative process of the return series and consequently explore how the variation in transaction volume could be a means of explaining the dynamics of exchange rates, firstly, and volatility, secondly.

4.2. Modeling Conditional Variance

To finalize the modeling of the return series for the two studied exchange rate pairs and based on the satisfactory results obtained in the previous section, we will proceed, as follows, to estimate the conditional variance equation associated with the mean equation.

According to our study, the ARMA process does not account for, on the one hand, the asymmetry in the series, and on the other hand, the varying amplitudes. ARCH models address the limitations of ARMA models by introducing persistence in the variance of errors. Thus, if volatility is high at time t, we also observe high volatility in the subsequent period.

The family of ARCH models can be divided into two subsets: linear ARCH models and non-linear ARCH models. Non-linear models rely on an asymmetric specification of disturbances, among which we can mention EGARCH (p, q) and TGARCH (p, q).

In the following, we will proceed as follows:

- Determination of p and q based on the autocorrelation of squared residuals.
- Estimation of the parameters of candidate models.
- Model validation.

From the results of the autocorrelation of squared residuals, we were able to identify the parameters of the GARCH model and thus, the candidate models for estimating the variance equation were determined.

Table 9:Results of determining significant lags

	p	**q**
EUR/TND	2	2
USD/TND	1	1

Source: My own estimations based on Eviews software

The results in the tables below show that models that have satisfied two necessary conditions for model validation: the significance of the parameters and the positivity of coefficients for linear models.

Table 10:The model validation of EUR/TND returns

	R-squared	**Log likelihood**	**Schwarz Criterion**	**Akaike info Criterion**
MA(1)-ARCH(1)	0.464963	-1325.234	1.942306	1.988634
MA(1)-ARCH(2)	0.482536	-1245.256	1.914312	1.985632
MA(1)-GARCH(1,1)	**0.494448**	**-1225.478**	**1.874305**	**1.858621**
MA(1)-GARCH(2,1)	****	****	****	****
MA(1)-GARCH(1,2)	****	****	****	****
MA(1)-GARCH(2,2)	****	****	****	****
MA(1)-EGARCH(1,1)	0.465010	-1230.789	1.912234	1.915463
MA(1)-GJR-GARCH(1,1)	0.465564	-1229.458	1.911156	1.919835

Source: My own estimations based on Eviews software

Table 11:The model validation of USD/TND returns

	R-squared	**Log likelihood**	**Schwarz Criterion**	**Akaike info Criterion**
ARMA(1,1)-ARCH(1)	0.462957	1037.452	1.635987	1.495642
ARMA(1,1)-GARCH(1,1)	0.472593	-1035.659	1.521894	1.495876
ARMA(1,1)-EGARCH(1,1)	**0.482852**	**-974.5973**	**1.495045**	**1.479361**
ARMA(1,1)-GJR-GARCH(1,1)	0.472365	-1020.365	1.499365	1.486547

Source: My own estimations based on Eviews software

We attempted to explore various lags up to t-2 in our study of the EUR/TND returns, but this empirical investigation was inconclusive due to the non-significance of the parameters or their lack of positivity. At first sight, we infer that GARCH (1,1) performs better than with GARCH models for the EUR/TND returns and the EGARCH (1,1) model holds the best forecasting accuracy criteria for the USD/TND returns.

After selecting the most effective model to describe the behavior of the return series for the two exchange rate pairs, we will present the estimation of the chosen models for both series.

4.3. The model estimation

4.3.1. The model estimation of the EUR/TND returns

The equation for an MA(1)-GARCH(1,1) model can be written as follows:

$$R_t = \theta_1 \varepsilon_{t-1} + \varepsilon_t$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2$$

Where,

- R_t reprents the dependent variable
- ε_t is the error term at time t
- σ_t^2 is the conditional variance of $\varepsilon_t$at time t,which s modelled by the GARCH(1,1) process.
- ω is a constant term representing the long-term average of conditional variance
- α_1 is the coefficient for the lagged squared error term ε_{t-1}^2. It captures the impact of past squared shocks on the current conditional variance.
- β_1 is the coefficient for the lagged squared conditional variance σ_{t-1}^2. It captures the persistence of conditional variance over time.

Table 12: Estimation of the selected model for the EUR/TND return series

	Coefficient	**P-value**
$\boldsymbol{\theta_1}$	-0.625796	0.0000
ω	1.16E-05	0.0000
$\boldsymbol{\alpha_1}$	0.229879	0.0000
$\boldsymbol{\beta_1}$	0.421663	0.0000
$\boldsymbol{\alpha_1 + \beta_1}$	0.651542	
Log likelihood	-1225.478	

Source: My own estimations based on Eviews software.

θ_1= −0.625796, a previous negative residual (ε_{t-1}) is associated with an increase in current return. This suggests that returns tend to adjust towards the mean in response to previous negative residuals.

α_1= 0.229879, This is the coefficient of the lagged squared error term in the conditional variance equation.

β_1= 0.421663, This is the coefficient of the lagged squared conditional variance σ_{t-1}^2 in the conditional variance equation. It captures the persistence of conditional variance over time. A higher value of β_1 implies that past conditional variances have a strong influence on the current conditional variance, indicating persistence in volatility. This indicates that conditional volatility has strong persistence. Past shocks in volatility have a significant influence on future EUR/TND volatility.

α_1 + β_1= 0.651542 A high persistence coefficient, such as 0.651542, indicates that conditional volatility has high persistence. This means that past shocks in volatility have a significant influence on the future volatility of the USD/TND returns series. In other words, a period of high volatility is likely to be followed by a period of high volatility, showing that changes in volatility tend to persist over time.

4.3.2. The model estimation of the USD/TND returns

The EGARCH model allows for asymmetric effects of past shocks on conditional volatility, capturing features like leverage effects commonly observed in financial time series data.

So, the ARMA(1,1)-EGARCH (1,1) model combines an autoregressive moving average model for the mean with an EGARCH model for the conditional volatility of the error term. It's a useful model for capturing both autocorrelation in returns and volatility clustering often observed in financial data.

The equation for an ARMA(1,1) model can be written as follows:

$$R_t = \emptyset_1 R_{t-1} + \theta_1 \varepsilon_{t-1} + \varepsilon_t$$

Where:

- R_t is the value of the time series at time 't.'
- c is a constant
- $\emptyset_1$ is the autoregressive coefficient of lag 1
- ε_t is the white noise error term at time t

- θ_1 is the moving average coefficient of lag 1
- ε_{t-1} is the white noise error term at time t-1

The EGARCH(1,1) process for conditional volatility is defined as:

$$\ln(\sigma_t^2) = \omega + \alpha_1 \left(\frac{|\varepsilon_{t-1}| + \gamma \varepsilon_{t-1}}{\sigma_{t-1}} \right) + \beta_1 ln(\sigma_{t-1}^2)$$

Where,

- $\ln(\sigma_t^2)$ represents the log conditional variance
- ω is the intercept term of EGARCH model
- α_1 is the EGARCH parameter that captures the asymmetric response to positive and negative shocks.
- ε_{t-1} is the lagged value of the error term at time t-1
- σ_{t-1} is the conditional standard deviation at time t-1
- β_1 is the EGARCH parameter that captures the persistence of volatility
- γ is the leverage parameter

The ARMA(1,1)-EGARCH(1,1) model combines autoregressive and moving average components for modeling the mean of the time series with an EGARCH component to capture the volatility dynamics.

Table 13:Estimation of the selected model for the USD/TND return series

	Coefficient	**P-value**
$\boldsymbol{\emptyset_1}$	0.312608	0.0006
$\boldsymbol{\theta_1}$	-0.588990	0.0000
ω	-1.432280	0.0000
$\boldsymbol{\alpha_1}$	0.357592	0.0000
$\boldsymbol{\beta_1}$	0.890468	0.0000
γ	-0.036668	0.0000
Log likelihood	-974.5973	

Source: My own estimations based on Eviews software

α_1: the ARCH term is statistically significant, it indicates that the size of the shock has a significant impact on the volatility of returns. If the ARCH term is positive, it suggests a positive relationship between past variance and current variance. This means that the larger the magnitude of the shock to the variance, the higher the volatility.

β_1: the GARCH term provides insights into the persistence of past volatility. When it is statistically significant, it indicates that past volatility helps predict volatility in the future.

The high value of this coefficient, compared to the alpha coefficient, indicates that the volatility of returns during the study period is very high and is expected to remain high during the next period. This phenomenon is known as volatility clustering. Additionally, since the sum of these two coefficients is very close to the value of 1, it suggests a strong persistence of volatility.

Indeed, volatility clustering implies that significant variations in returns are typically followed by significant variations, leading to the clustering of extremes into volatility clusters or groups. This challenges the assumption of homoscedasticity commonly adopted in linear econometrics.

γ : the analysis of the coefficient related to asymmetry in this model, which reveals a negative coefficient, confirms its existence, as the term lambda is negative. In other words, returns exhibit higher volatility in the event of a negative shock on returns compared to the volatility in the event of a positive shock on returns.

In the following sections, we will examine the relationship between the trading volume and the series of exchange rate returns studied earlier. We will test whether the trading volume in the Tunisian market significantly influence the exchange rates of the studied currency pairs.

5. The Volume-Return Relationship in the Tunisian Foreign Exchange Market

The study carried out has enabled us to reveal and identify the process that generates the series of returns that are the subject of our empirical investigation. In what follows, we will, highlight the relationship between the exchange rates (USD/TND and EUR/TND) and the trading volume, which remains one of the main components of the microstructure approach. For, as we have already shown in the first chapter, volume can be a means of conveying the private information held by the various interbank foreign exchange market.

In the following section, we will begin by testing the causality between trading volume and the returns of each exchange rate. Then, we will use the price series generating process identified in the previous section by incorporating the volume change variable first into the mean equation and then into the variance equation. This will allow us to observe the effect of and volatility on the exchange rate dynamics.

5.1. Causality test between the trading volume and the exchange rate return

Chaung and lee (2006) used a granger causality test between profitability and trading volume. we will check whether there is a positive relationship between positive profitability obtained by financial players and trading volume by means of a granger causality test.

Econometrically, a granger causality test consists in checking whether the past values of an exogenous variable x contribute to obtaining a more accurate forecast of a second endogenous variable y.

In our study, we intend to test the following causality test:

$$V_t = \alpha_{11} + \sum_{j=1}^{p} \beta_{11j}\, V_{t-j} + \sum_{j=1}^{p} \beta_{12j} R_{t-j} + \varepsilon_{1t}$$

$$R_t = \alpha_{21} + \sum_{j=1}^{p} \beta_{21j} V_{t-j} + \sum_{j=1}^{p} \beta_{22j} R_{t-j} + \varepsilon_{2t}$$

- V_t : trading volume
- R_t : the exchange rate returns
- V_{t-j} : lagged trading volume
- R_{t-j} : lagged returns
- $\varepsilon_{1t}, \varepsilon_{2t}$ error residuals
- p : Number of lags chosen based on AIC and SC criteria

Rejecting the null hypothesis ($\beta_{12j} = 0\, por\ tout\ j$) means accepting that positive returns obtained by investors Granger-cause excessive trading volume.

According to Chuang and Lee (2006), rejecting the null hypothesis (β_{21j} = 0,pour tout j) meaning that transaction volume does not Granger-cause positive returns, highlights a situation of inefficiency in the foreign exchange market.

To test the existence of a causal link from the returns obtained by investors to the trading volume conducted by them, we must first implement a VAR (Vector Autoregressive) model between

Rt and Vt Our VAR model was constructed with a lag order equal to 4, as it minimizes the Schwarz criterion.

Table 14:Granger causality test

		Chi-squared statistic	**probability**
EUR/TND	R_t does not cause V_t	5.2245	0.0236
	V_t does not cause R_t	1.01916	0.2460
USD/TND	R_t does not cause V_t	2.47625	0.0426
	V_t does not cause R_t	1.09064	0.3597

Source: My own estimations based on Eviews software

An examination of the table above shows that the null hypothesis of the Granger test is rejected for both exchange rate returns at the 5% significance level.

It can be inferred that a unidirectional, positive causal relationship exists in the Granger sense, running from profitability to trading volume. Conversely, an examination of the reverse direction of the test indicates that the null hypothesis, which posits that excessive trading volume does not lead to positive returns, is accepted at the 5% significance level. Consequently, the Granger test reveals a one-way association, where positive returns appear to influence an increase in trading volume. This phenomenon can be attributed to the notion that investors, upon achieving positive returns, gain greater confidence in their ability to make sound trading decisions, thereby leading to a heightened level of trading activity.In addition, in the forex context, transactions are often driven by news or expectations of future returns. Traders and investors place orders in response to new information or changes in exchange rates, which can lead to variations in volume. In other words, volume is often a consequence of returns, rather than a direct cause.

In the Tunisian exchange market, trading volume appears to lack informative content and does not seem to exert a direct influence on prices. Instead, it is the returns that have a discernible impact on trading volume. This phenomenon can be attributed to several factors. Firstly, the existence of restrictions on the movement of foreign currencies can significantly limit the ability of market participants to engage in large-scale transactions, thus constraining their capacity to influence exchange rates through volume. Consequently, trading volumes may remain relatively stable or subject to regulatory measures, curbing their capacity to directly shape returns. Secondly, Bank transactions are typically linked to treasury management operations and are not necessarily driven by signals related to expected returns.

Indeed, Chen (2001), Sabri (2008), Mpofu (2012) and Kudryavtsev (2017) are consistent with our findings, demonstrating that returns influence the trading volume, with a more pronounced causality observed from returns to volume.

5.2. The generating process of the Volume-Return Relationship in the Tunisian Foreign Exchange Market

The stationarity of the series has been demonstrated in the second section of this chapter, which allows us to potentially use this model (1):

$$R_t = \alpha_0 \varepsilon_{t-1} + \alpha_1 V_t + \varepsilon_1$$

$$\sigma_t^2 = \omega + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2 \text{ (1)}$$

$$R_t = \emptyset_1 R_{t-1} + \theta_1 \varepsilon_{t-1} + \alpha_1 V_t + \varepsilon_t$$

$$\ln(\sigma_t^2) = \omega + \alpha_1 \left(\frac{|\varepsilon_{t-1}| + \gamma \varepsilon_{t-1}}{\sigma_{t-1}}\right) + \beta_1 ln(\sigma_{t-1}^2) \text{ (2)}$$

Equation (1): Conditional variance equation expressed by a GARCH (1,1) process for the EUR/TND pair.

Equation (2): Conditional variance equation expressed by an EGARCH (1,1) process for the USD/TND pair.

This model will allow us to study the impact of volume variations on the returns of exchange rate series in the Tunisian market

Table 15:Model Estimation EUR/TND

	Coefficient	**P-value**
$\boldsymbol{\alpha_1}$	0.12599	0.1120
$\boldsymbol{\theta_1}$	-0.621607	0.0000
ω	1.19E-05	0.0000
$\boldsymbol{\beta_1}$	0.234715	0.0000
$\boldsymbol{\beta_2}$	0.410425	0.0000
$\boldsymbol{\beta_1}$+ $\boldsymbol{\beta_2}$	0,64514	
Log likelihood	-972.6884	

Source: My own estimations based on Eviews software

Table 16: Model Estimation USD/TND

	Coefficient	**P-value**
$\boldsymbol{\alpha_1}$	0.002565	0.2150
$\emptyset_1$	0.314398	0.0006
$\boldsymbol{\theta_1}$	-0.590841	0.0005
ω	-1.451343	0.0000
α	0.360164	0.0000
β	0.888887	0.0000
γ	-0.034327	0.0000
Log likelihood	-1023.273	

Source: My own estimations based on Eviews software

The observed unidirectional causality between exchange returns and trading volume in the granger causality test infers that movements in returns exert a notable influence on the level of trading activity. This suggests a scenario where historical returns shape market participants' behaviors, contributing to fluctuations in trading volume. Contrarily, the examination of the reverse relationship, aiming to unveil whether changes in trading volume significantly impact subsequent exchange returns, presents a contradictory finding. Despite the clear influence of returns on volume, the analysis fails to yield statistically significant evidence supporting the idea that volume actively influences future returns within the chosen model($\boldsymbol{\alpha_1}$ is unsignificant). This contradiction underscores a complex and possibly asymmetric relationship between volume and returns, where while returns might steer trading activity, the impact of volume on subsequent returns appears less evident or potentially influenced by unaccounted factors.

Indeed, the non-significant coefficient for the EUR/TND and USD/TND pairs in the Tunisian exchange market can be attributed to a combination of factors inherent to the market's unique structure. Firstly, the lack of dynamism in the Tunisian exchange market implies that trading activities may not experience frequent or significant changes. In a less dynamic environment, the influence of returns on trading volume may be diminished, as market participants may not be as responsive to fluctuations in returns.

Moreover, the presence of few significant participants in the market can contribute to the non-significant relationship. If a small number of major players dominate the market, their actions may carry more weight than the overall trading volume, overshadowing the potential impact of returns on trading activity. In such a scenario, the trading decisions of these major participants could be the primary driver of market movements, rendering the influence of returns less notable.

Additionally, the intervention of the regulator, CBT, could be a significant factor contributing to the non-significant relationship between returns and trading volume in the USD/TND pair within the Tunisian exchange market. Regulatory interventions are designed to ensure market stability, and maintain the integrity of the financial system.

The cyclical nature of the balance of payments also plays a significant role in understanding the impact of volume on returns. Presently, the Tunisian foreign exchange market tends to lack dynamism and primarily shows a unidirectional movement.

Indeed, in less dynamic markets like Tunisia's, for instance, when the balance of payments is inclined towards currency buying, the effect of trading volume on these fluctuations is somewhat restricted. The dominant trend of currency selling or buying, especially in the absence of a more balanced market with active buyers, can often overshadow the immediate impact of trading volume. Thus, traders and investors might find that the primary driving forces behind exchange rate movements in such markets are the broader economic factors related to balance of payments, rather than the trading volume itself. In more active and balanced markets, buying and selling activities are spread more evenly, typically involving a larger number of participants on both sides of the trade. This balance in participation helps stabilize exchange rates, as shifts in supply and demand tend to be less abrupt. However, in less dynamic markets, as described, the imbalance between buyers and sellers can result in more substantial and rapid fluctuations in exchange rates. This cyclical nature, influenced by the balance of payments, adds another layer to the nuanced relationship between volume and returns in the forex market.

6. The Volume-Volatility Relationship in the Tunisian Foreign Exchange Market

The relationship between trading volume and price volatility is a significant and extensively studied topic in financial literature. Microstructure literature consistently demonstrates a strong and positive connection between trading volume and volatility.

In this section, we aim to analyze the influence of trading activity on exchange rate dynamics. To accurately estimate this relationship, we will adopt the following models:

$$\sigma_t^2 = \omega + \beta_1 \varepsilon_{t-1}^2 + \beta_2 \sigma_{t-1}^2 + \beta_3 V_t \ (1)$$

$$\ln(\sigma_t^2) = \omega + \alpha_1 \left(\frac{|\varepsilon_{t-1}| + \gamma \varepsilon_{t-1}}{\sigma_{t-1}}\right) + \beta_1 ln(\sigma_{t-1}^2) \ + \beta_2 V_t \ (2)$$

Equation (1): Conditional variance equation expressed by a GARCH (1,1) process for the EUR/TND pair.

Equation (2): Conditional variance equation expressed by an EGARCH (1,1) process for the USD/TND pair.

Table 17:Model Estimation EUR/USD volume-volatility

	Coefficient	**P-value**
$\boldsymbol{\theta_1}$	0.050000	0.0000
ω	5.67E-05	0.0000
$\boldsymbol{\beta_1}$	0.150000	0.0000
$\boldsymbol{\beta_2}$	0.600000	0.0000
$\boldsymbol{\beta_3}$	0.025600	0.0000
Log likelihood	-1031.908	

Source: My own estimations based on Eviews software

Table 18:Model Estimation USD/TND volume-volatility

	Coefficient	**P-value**
$\emptyset_1$	0.291175	0.0000
$\boldsymbol{\theta_1}$	-0.566414	0.0020
ω	-1.424171	0.0000
$\boldsymbol{\alpha_1}$	0.349172	0.0000
$\boldsymbol{\beta_1}$	0.882763	0.0000
γ	-0.025550	0.0000
$\boldsymbol{\beta_2}$	0.002565	0.0001
Log likelihood	-1158.461	

Source: My own estimations based on Eviews software

The GARCH(1,1) and EGARCH (1,1) estimation results for the relationship between trading volume and exchange rate volatility in the USD/TND and EUR/TND exchange rate market provide intriguing insights. Notably, a positive coefficient emerges when examining how trading volume and exchange rate volatility relate in Tunisia, with exchange rate returns driving trading volume. The positive coefficient implies that as trading volume increases, there's a parallel rise in conditional variance or heightened volatility. This linkage suggests that increased trading activity aligns with more pronounced fluctuations within the market model. These fluctuations might stem from escalated uncertainty or heightened market activity levels. Such trends could indicate the infusion of new information into asset prices or shifts in liquidity conditions impacting market dynamics. Essentially, the positive coefficient highlights a connection between trading volume and increased volatility, underlining how market activity might influence fluctuations, reflecting shifts in information or liquidity within the market.

β_1 coefficient is positive, these results indicate that historical patterns of volatility have a more pronounced impact on predicting forthcoming volatility. This may suggest that traders and market participants are influenced by previous volatility trends when making decisions in this market, potentially reflecting a reliance on past information to anticipate future market conditions.

It's worth noting, that our findings are in line with the results of Mahajan and Singh (2009), who found a positive and statistically significant relationship between volume and volatility, our findings diverge. Additionally, our results align with the research conducted by Gervais and al. (2001), which suggests that periods of consistently high (or low) trading volumes over a day or week tend to correspond with significant (or minimal) returns over the subsequent month.

However, our findings differ with the empirical conclusions of Miseman (2019), whose work suggests that volume has limited predictive power regarding future return dynamics.

In the dynamic landscape of financial markets, Recognizing the impact of information asymmetry among market participants, adaptive strategies that leverage advanced data analysis techniques should be embraced. Traders should be attuned to the persistence of volatility dynamics, anticipating prolonged periods of high volatility for more effective risk management. Given the Tunisian Dinar's inclusion in a currency basket dominated by the Euro and the United States Dollar, close monitoring of variations in the EUR/USD exchange rate is crucial.

In response to the persistent volatility observed in the Tunisian foreign exchange market, traders are advised to focus on adaptive strategies that accommodate extended periods of heightened volatility. Diversification across various currency pairs or asset classes remains a prudent approach to spread risk exposure across different market dynamics. Vigilance, adaptability, and ongoing analysis of volatility patterns should guide traders in fine-tuning their strategies to effectively respond to the ever-evolving market conditions.

Considering the influence of market structure and regulatory interventions by the Central Bank of Tunisia is pivotal for adapting trading strategies. In markets with fewer dynamics and imbalances in buyer-seller ratios, traders must remain adaptable to cope with swift fluctuations in exchange rates. Furthermore, staying updated on technological advancements, unconventional monetary policies, and geopolitical factors affecting exchange rates is critical. Engaging in comparative analyses with other emerging markets can offer valuable insights, aiding in the refinement of adaptable trading strategies tailored to various market conditions and trends.

7. Conclusion

This chapter aimed to provide evidence of the impact of trading volume and volatility on exchange rate returns. The literature review established these variables as determinants of exchange rate returns. Estimation results revealed a unidirectional relationship, where positive returns influenced an increase in trading volume. Conversely, the relationship in the opposite direction indicated that elevated trading volume did not guarantee positive returns. To gain deeper insights, GARCH and EGARCH models were constructed. These models suggested that the EUR/TND and USD/TND pairs did not exhibit a significant relationship between trading volume and returns, influenced by factors like limited market transparency and participant composition.

Furthermore, The non-significant coefficient in the Tunisian exchange market for the EUR/TND and USD/TND pairs stems from inherent market characteristics. The market's limited dynamism implies infrequent trading changes, reducing the responsiveness of trading volume to return fluctuations. Few major market participants could outweigh overall volume influence, rendering return impact less significant. Regulatory interventions from the CBT also contribute, aiming for market stability. The cyclical nature of the balance of payments further restricts volume effects on returns. In less dynamic markets like Tunisia, where currency buying or selling dominates, trading volume's immediate impact is often overshadowed by prevailing trends, especially without active buyers balancing the market.

Additionnaly, The presence of a positive coefficient in a model linking trading volume to volatility implies that heightened trading likely corresponds to increased market volatility, potentially driven by amplified uncertainty or greater overall market activity. This relationship suggests that intensified trading may lead to more significant fluctuations, signaling shifts in market information or liquidity conditions.

CONCLUSION

The abandonment of macroeconomic theories to explain short-term exchange rate dynamics was initiated by researchers Meese and Rogof in (1983) who demonstrated the failure of macroeconomic approaches to explain short-term exchange rates. Thus, international finance has experienced the emergence of another school of thought: Microstructure.

In fact, in the macroeconomic approach, the determination of the equilibrium price was purely based on the interaction of supply and demand, while the microstructural approach incorporates other variables that influence the behavior of the price, namely, trading volume, volatility, order flow and spreads.

The microstructure of foreign exchange markets tries to better understand the information embedded in trading volume that directly influences the dynamic processes of price changes. This approach has been able to surpass macroeconomic models, especially since the markets are inefficient, more precisely, all agents and participants in the foreign exchange market do not have access to the same information, even less the same motivations and objectives.

In this comprehensive study of the Tunisian foreign exchange market, we conducted a thorough analysis of its microstructure to understand the dynamics of exchange rate volatility and the relationship between trading volume and exchange rate returns which are pivotal variables governing market dynamics. Our analysis focused on two major currency pairs, EUR/TND and USD/TND, using GARCH(1,1) and EGARCH(1,1) models, respectively. The key findings shed light on the nuanced relationships between these variables, providing valuable insights for both academics and practitioners in the field of financial markets.

The results of our analysis have unveiled several noteworthy findings, shedding light on the relationship between trading volume, exchange rate returns, and volatility. We employed the GARCH(1,1) model to study EUR/TND, revealing that conditional volatility exhibits strong persistence. Notably, past shocks in volatility exert a significant influence on future USD/TND volatility, indicating the enduring nature of volatility dynamics. In essence, periods of high volatility are prone to be followed by additional periods of high volatility, underlining the lasting impact of volatility changes.

Shifting our focus to the model estimation for USD/TND using the EGARCH(1,1) model, we uncovered several essential findings. The size of the shock emerged as a critical factor significantly impacting return volatility. Moreover, past volatility emerged as a reliable predictor of future volatility, with a noteworthy observation that return volatility during our study period was exceedingly high. This phenomenon is expected to persist into the next period, a phenomenon known as volatility clustering. Furthermore, we observed that returns exhibited higher volatility in the event of a negative shock compared to a positive one.

When examining the evolution of the exchange rates, a fundamental explanation for these fluctuations lies in the fact that the Tunisian Dinar is part of a currency basket, with the Euro and the United States Dollar being the dominant constituents in terms of weight. As a result, variations in the EUR/USD exchange rate significantly influence the overall value of this currency basket.

Next, we explored the Volume-Return Relationship in the Tunisian Foreign Exchange Market. Our causality tests revealed a unidirectional, positive causal relationship, running from returns to trading volume. Intriguingly, excessive trading volume did not necessarily lead to positive returns. Instead, it became apparent that positive returns played a pivotal role in stimulating an increase in trading volume. This complex relationship can be attributed to the confidence which boost investors experience upon achieving positive returns, consequently leading to heightened trading activity. Moreover, constraints on the movement of foreign currencies limited the ability of market participants to engage in large-scale transactions, indirectly influencing exchange rates through volume. Additionally, the substantial foreign currency reserves maintained by banks, which hold a central role in the foreign exchange market, had their own unique impact.

Afterwards, we delved into the generating process of the Volume-Return Relationship, Our examination applied GARCH(1,1) to EUR/TND and EGARCH(1,1) to USD/TND, revealing non-significant volume coefficients. In the Tunisian exchange market, the market's lack of dynamism and dominance by few major participants diminishes the impact of returns on trading volume. Regulatory interventions by the Central Bank of Tunisia (CBT) also play a role in shaping this relationship, aiming to ensure market stability. The cyclical nature of the balance of payments in the Tunisian foreign exchange market, characterized by unidirectional movements, further affects the relationship between volume and returns. In less dynamic markets, the imbalance between buyers and sellers, influenced by the dominant trend in the balance of payments, can lead to substantial and rapid fluctuations in exchange rates.

Furthermore, our investigation into the volume-volatility relationship has unveiled a positive relationship. This suggests that when a positive coefficient emerges in a model, such as a regression where trading volume serves as a predictor variable for conditional variance, it signifies a noteworthy relationship. Specifically, the positive coefficient suggests that an increase in trading volume is associated with higher conditional variance or increased volatility. This association might indicate that heightened trading activity corresponds to more pronounced market fluctuations within the model. Such fluctuations could be a result of increased uncertainty or higher levels of market activity.

The primary implication of our findings for foreign exchange market participants involves leveraging the persistent nature of volatility, characterized by volatility clustering, to forecast currency fluctuations. Additionally, the observed unidirectional causal relationship. Traders in the Tunisian foreign exchange market should acknowledge the one-way link between positive returns and amplified trading volume, understanding that increased trading activity doesn't guarantee positive returns consistently. Moreover, our results indicate the potential use of trading volume to forecast future volatility states.

Certain directions for future research include comparative analyses with other emerging markets can provide valuable comparative insights. Additionally, exploring the influence of technological advancements on trading behavior and examining the effects of unconventional monetary policies and geopolitical factors on exchange rate dynamics are important avenues for further investigation, contributing to a more comprehensive understanding of the Tunisian foreign exchange market.

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APPENDICES

Appendix 1:Preliminary Tests

Date: 09/20/23 Time: 21:13
Sample: 1/01/2019 9/20/2023

	USD/TND	VOLUME
Mean	2.925149	51319.66
Median	2.879600	50131.50
Maximum	3.315000	158004.0
Minimum	2.673700	9.000000
Std. Dev.	0.154499	27577.90
Skewness	0.362329	0.353432
Kurtosis	2.028068	3.019652
Jarque-Bera	75.44875	25.66885
Probability	0.000000	0.000003
Sum	3603.783	63225827
Sum Sq. Dev.	29.38391	9.36E+11
Observations	1232	1232

Date: 09/19/23 Time: 20:52
Sample: 1/01/2019 9/12/2023

	TRADING VO	EUR/TND
Mean	63646.44	3.261975
Median	60973.00	3.259750
Maximum	203561.0	3.518700
Minimum	3.141400	3.082500
Std. Dev.	30120.68	0.082196
Skewness	0.748578	0.244495
Kurtosis	4.263200	2.681463
Jarque-Bera	196.0144	17.39778
Probability	0.000000	0.000167
Sum	78030535	3999.182
Sum Sq. Dev.	1.11E+12	8.276272
Observations	1226	1226

Augmented Dickey-Fuller Unit Root Test on RTC

Null Hypothesis: RTC has a unit root
Exogenous: Constant
Lag Length: 2 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-30.98010	0.0000
Test critical values:	1% level	-3.435488	
	5% level	-2.863697	
	10% level	-2.567968	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RTC)
Method: Least Squares
Date: 09/19/23 Time: 21:01
Sample (adjusted): 1/07/2019 9/12/2023
Included observations: 1222 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RTC(-1)	-2.037921	0.065782	-30.98010	0.0000
D(RTC(-1))	0.485882	0.048282	10.06346	0.0000
D(RTC(-2))	0.145412	0.025788	5.638721	0.0000
C	-7.07E-06	0.000166	-0.042645	0.9660

R-squared	0.730766	Mean dependent var	-3.04E-06
Adjusted R-squared	0.730103	S.D. dependent var	0.011153
S.E. of regression	0.005794	Akaike info criterion	-7.460583
Sum squared resid	0.040894	Schwarz criterion	-7.443862
Log likelihood	4562.416	Hannan-Quinn criter.	-7.454290
F-statistic	1101.981	Durbin-Watson stat	2.027053
Prob(F-statistic)	0.000000		

Augmented Dickey-Fuller Unit Root Test on RTC

Null Hypothesis: RTC has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-31.00771	0.0000
Test critical values:	1% level	-3.965574	
	5% level	-3.413493	
	10% level	-3.128792	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RTC)
Method: Least Squares
Date: 09/19/23 Time: 21:00
Sample (adjusted): 1/07/2019 9/12/2023
Included observations: 1222 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RTC(-1)	-2.040205	0.065797	-31.00771	0.0000
D(RTC(-1))	0.487299	0.048287	10.09168	0.0000
D(RTC(-2))	0.146172	0.025791	5.667528	0.0000
C	-0.000355	0.000333	-1.066446	0.2864
@TREND("1/01/2019")	5.66E-07	4.70E-07	1.205071	0.2284

R-squared	0.731087	Mean dependent var	-3.04E-06
Adjusted R-squared	0.730203	S.D. dependent var	0.011153
S.E. of regression	0.005793	Akaike info criterion	-7.460139
Sum squared resid	0.040846	Schwarz criterion	-7.439238
Log likelihood	4563.145	Hannan-Quinn criter.	-7.452273
F-statistic	827.1555	Durbin-Watson stat	2.027872
Prob(F-statistic)	0.000000		

Null Hypothesis: RTCUSD has a unit root
Exogenous: Constant
Lag Length: 1 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-31.50205	0.0000
Test critical values:	1% level	-3.435458	
	5% level	-2.863683	
	10% level	-2.567961	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RTCUSD)
Method: Least Squares
Date: 09/20/23 Time: 21:14
Sample (adjusted): 1/04/2019 9/20/2023
Included observations: 1229 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RTCUSD(-1)	-1.326351	0.042104	-31.50205	0.0000
D(RTCUSD(-1))	0.089145	0.026411	3.375312	0.0008
C	5.55E-05	0.000152	0.365220	0.7150

R-squared	0.613869	Mean dependent var	-8.32E-06
Adjusted R-squared	0.613240	S.D. dependent var	0.008564
S.E. of regression	0.005326	Akaike info criterion	-7.629943
Sum squared resid	0.034779	Schwarz criterion	-7.617460
Log likelihood	4691.600	Hannan-Quinn criter.	-7.625246
F-statistic	974.5460	Durbin-Watson stat	2.025238
Prob(F-statistic)	0.000000		

Augmented Dickey-Fuller Unit Root Test on RTC

Null Hypothesis: RTC has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 2 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-31.00771	0.0000
Test critical values:	1% level	-3.965574	
	5% level	-3.413493	
	10% level	-3.128792	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(RTC)
Method: Least Squares
Date: 09/19/23 Time: 21:00
Sample (adjusted): 1/07/2019 9/12/2023
Included observations: 1222 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
RTC(-1)	-2.040205	0.065797	-31.00771	0.0000
D(RTC(-1))	0.487299	0.048287	10.09168	0.0000
D(RTC(-2))	0.146172	0.025791	5.667528	0.0000
C	-0.000355	0.000333	-1.066446	0.2864
@TREND("1/01/2019")	5.66E-07	4.70E-07	1.205071	0.2284

R-squared	0.731087	Mean dependent var	-3.04E-06
Adjusted R-squared	0.730203	S.D. dependent var	0.011153
S.E. of regression	0.005793	Akaike info criterion	-7.460139
Sum squared resid	0.040846	Schwarz criterion	-7.439238
Log likelihood	4563.145	Hannan-Quinn criter.	-7.452273
F-statistic	827.1555	Durbin-Watson stat	2.027872
Prob(F-statistic)	0.000000		

Augmented Dickey-Fuller Unit Root Test on VOLUME

Null Hypothesis: VOLUME has a unit root
Exogenous: Constant
Lag Length: 11 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.792831	0.0001
Test critical values:	1% level	-3.435523	
	5% level	-2.863712	
	10% level	-2.567977	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(VOLUME)
Method: Least Squares
Date: 10/25/23 Time: 16:17
Sample (adjusted): 1/17/2019 9/12/2023
Included observations: 1214 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
VOLUME(-1)	-0.124236	0.025921	-4.792831	0.0000
D(VOLUME(-1))	-0.169353	0.035694	-4.744515	0.0000
D(VOLUME(-2))	-0.333913	0.035995	-9.276677	0.0000
D(VOLUME(-3))	-0.232487	0.036432	-6.381477	0.0000
D(VOLUME(-4))	-0.295991	0.036194	-8.177927	0.0000
D(VOLUME(-5))	0.040087	0.036444	1.099984	0.2716
D(VOLUME(-6))	-0.196499	0.035255	-5.573713	0.0000
D(VOLUME(-7))	-0.130561	0.035601	-3.667318	0.0003
D(VOLUME(-8))	-0.142466	0.033686	-4.229202	0.0000
D(VOLUME(-9))	-0.149307	0.032356	-4.614538	0.0000
D(VOLUME(-10))	0.077334	0.029735	2.600772	0.0094
D(VOLUME(-11))	-0.081494	0.028603	-2.849137	0.0045
C	7905.502	1743.623	4.533950	0.0000

R-squared	0.340345	Mean dependent var	-2.661450
Adjusted R-squared	0.333754	S.D. dependent var	23625.46
S.E. of regression	19284.02	Akaike info criterion	22.58259
Sum squared resid	4.47E+11	Schwarz criterion	22.63722
Log likelihood	-13694.63	Hannan-Quinn criter.	22.60316
F-statistic	51.63739	Durbin-Watson stat	1.998641
Prob(F-statistic)	0.000000		

Augmented Dickey-Fuller Unit Root Test on VOLUME

Null Hypothesis: VOLUME has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 11 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-4.902885	0.0003
Test critical values:	1% level	-3.965623	
	5% level	-3.413518	
	10% level	-3.128806	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(VOLUME)
Method: Least Squares
Date: 10/25/23 Time: 16:13
Sample (adjusted): 1/17/2019 9/12/2023
Included observations: 1214 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
VOLUME(-1)	-0.129103	0.026332	-4.902885	0.0000
D(VOLUME(-1))	-0.165480	0.035883	-4.611634	0.0000
D(VOLUME(-2))	-0.330101	0.036176	-9.124813	0.0000
D(VOLUME(-3))	-0.229165	0.036567	-6.266913	0.0000
D(VOLUME(-4))	-0.293082	0.036298	-8.074224	0.0000
D(VOLUME(-5))	0.042620	0.036522	1.166957	0.2435
D(VOLUME(-6))	-0.194168	0.035323	-5.496905	0.0000
D(VOLUME(-7))	-0.128514	0.035653	-3.604569	0.0003
D(VOLUME(-8))	-0.140798	0.033722	-4.175192	0.0000
D(VOLUME(-9))	-0.147998	0.032378	-4.570864	0.0000
D(VOLUME(-10))	0.078065	0.029742	2.624744	0.0088
D(VOLUME(-11))	-0.080873	0.028608	-2.826945	0.0048
C	9256.971	2167.851	4.270115	0.0000
@TREND("1/01/2019")	-1.683129	1.604405	-1.049067	0.2944

R-squared	0.340949	Mean dependent var	-2.661450
Adjusted R-squared	0.333810	S.D. dependent var	23625.46
S.E. of regression	19283.21	Akaike info criterion	22.58332
Sum squared resid	4.46E+11	Schwarz criterion	22.64216
Log likelihood	-13694.08	Hannan-Quinn criter.	22.60547
F-statistic	47.75393	Durbin-Watson stat	1.998495
Prob(F-statistic)	0.000000		

Null Hypothesis: VOLUME has a unit root
Exogenous: Constant
Lag Length: 9 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.448177	0.0000
Test critical values:	1% level	-3.435488	
	5% level	-2.863697	
	10% level	-2.567968	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(VOLUME)
Method: Least Squares
Date: 10/25/23 Time: 16:34
Sample (adjusted): 1/15/2019 9/20/2023
Included observations: 1222 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
VOLUME(-1)	-0.173320	0.031812	-5.448177	0.0000
D(VOLUME(-1))	-0.273224	0.038365	-7.121632	0.0000
D(VOLUME(-2))	-0.337657	0.038143	-8.852479	0.0000
D(VOLUME(-3))	-0.238092	0.038050	-6.257366	0.0000
D(VOLUME(-4))	-0.222261	0.037439	-5.936582	0.0000
D(VOLUME(-5))	-0.072842	0.037325	-1.951533	0.0512
D(VOLUME(-6))	-0.160156	0.035599	-4.498943	0.0000
D(VOLUME(-7))	-0.173643	0.033842	-5.130956	0.0000
D(VOLUME(-8))	-0.132853	0.030861	-4.304935	0.0000
D(VOLUME(-9))	-0.177313	0.028338	-6.257067	0.0000
C	8872.651	1741.219	5.095653	0.0000

R-squared	0.269154	Mean dependent var	-30.81997
Adjusted R-squared	0.263118	S.D. dependent var	24034.50
S.E. of regression	20631.65	Akaike info criterion	22.71600
Sum squared resid	5.15E+11	Schwarz criterion	22.76198
Log likelihood	-13868.48	Hannan-Quinn criter.	22.73331
F-statistic	44.59828	Durbin-Watson stat	1.992907
Prob(F-statistic)	0.000000		

Null Hypothesis: VOLUME has a unit root
Exogenous: Constant, Linear Trend
Lag Length: 9 (Automatic - based on SIC, maxlag=22)

		t-Statistic	Prob.*
Augmented Dickey-Fuller test statistic		-5.548709	0.0000
Test critical values:	1% level	-3.965574	
	5% level	-3.413493	
	10% level	-3.128792	

*MacKinnon (1996) one-sided p-values.

Augmented Dickey-Fuller Test Equation
Dependent Variable: D(VOLUME)
Method: Least Squares
Date: 10/25/23 Time: 16:38
Sample (adjusted): 1/15/2019 9/20/2023
Included observations: 1222 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
VOLUME(-1)	-0.178384	0.032149	-5.548709	0.0000
D(VOLUME(-1))	-0.269145	0.038545	-6.982591	0.0000
D(VOLUME(-2))	-0.334079	0.038281	-8.726927	0.0000
D(VOLUME(-3))	-0.235001	0.038153	-6.159452	0.0000
D(VOLUME(-4))	-0.219649	0.037513	-5.855243	0.0000
D(VOLUME(-5))	-0.070684	0.037375	-1.891191	0.0588
D(VOLUME(-6))	-0.158303	0.035637	-4.442154	0.0000
D(VOLUME(-7))	-0.172215	0.033865	-5.085346	0.0000
D(VOLUME(-8))	-0.131965	0.030869	-4.274978	0.0000
D(VOLUME(-9))	-0.176792	0.028340	-6.238247	0.0000
C	10275.04	2166.253	4.743231	0.0000
@TREND("1/01/2019")	-1.839864	1.690977	-1.088048	0.2768

R-squared	0.269868	Mean dependent var	-30.81997
Adjusted R-squared	0.263230	S.D. dependent var	24034.50
S.E. of regression	20630.09	Akaike info criterion	22.71666
Sum squared resid	5.15E+11	Schwarz criterion	22.76682
Log likelihood	-13867.88	Hannan-Quinn criter.	22.73554
F-statistic	40.65767	Durbin-Watson stat	1.992899
Prob(F-statistic)	0.000000		

Appendix 2:Correlogramme

Date: 10/04/23 Time: 09:56
Sample: 1/01/2019 9/12/2023
Included observations: 1225

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.423	-0.423	219.33	0.000
		2	-0.068	-0.300	224.95	0.000
		3	0.036	-0.171	226.53	0.000
		4	0.023	-0.075	227.17	0.000
		5	-0.030	-0.065	228.28	0.000
		6	-0.017	-0.073	228.65	0.000
		7	-0.004	-0.078	228.67	0.000
		8	0.037	-0.019	230.39	0.000
		9	-0.023	-0.024	231.03	0.000
		10	-0.032	-0.061	232.27	0.000
		11	0.056	0.005	236.19	0.000
		12	-0.019	-0.004	236.63	0.000
		13	0.002	0.010	236.63	0.000
		14	0.002	0.013	236.64	0.000
		15	-0.003	0.005	236.65	0.000
		16	-0.003	-0.001	236.66	0.000
		17	-0.002	-0.005	236.67	0.000
		18	0.039	0.052	238.53	0.000
		19	-0.044	0.000	240.93	0.000
		20	0.016	0.012	241.25	0.000
		21	-0.057	-0.073	245.31	0.000
		22	0.076	0.010	252.46	0.000
		23	-0.011	0.022	252.62	0.000
		24	-0.030	-0.006	253.73	0.000
		25	0.042	0.037	255.90	0.000
		26	-0.051	-0.038	259.18	0.000
		27	0.039	0.011	261.14	0.000
		28	-0.008	0.008	261.23	0.000
		29	0.008	0.023	261.31	0.000
		30	-0.021	-0.006	261.86	0.000
		31	0.009	-0.008	261.95	0.000
		32	-0.006	-0.004	261.99	0.000
		33	0.018	0.011	262.38	0.000
		34	-0.014	0.006	262.61	0.000
		35	-0.012	-0.018	262.81	0.000
		36	0.049	0.036	265.88	0.000

Date: 10/03/23 Time: 21:09
Sample: 1/01/2019 9/20/2023
Included observations: 1231

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	-0.176	-0.176	38.193	0.000
		2	-0.047	-0.081	40.968	0.000
		3	-0.026	-0.051	41.788	0.000
		4	0.022	0.004	42.404	0.000
		5	-0.024	-0.025	43.131	0.000
		6	-0.048	-0.059	45.965	0.000
		7	0.008	-0.015	46.052	0.000
		8	-0.016	-0.028	46.369	0.000
		9	0.024	0.013	47.113	0.000
		10	-0.037	-0.034	48.815	0.000
		11	0.022	0.007	49.420	0.000
		12	0.013	0.013	49.622	0.000
		13	0.010	0.013	49.748	0.000
		14	-0.004	0.003	49.773	0.000
		15	0.018	0.021	50.191	0.000
		16	0.043	0.050	52.472	0.000
		17	-0.017	0.006	52.850	0.000
		18	-0.036	-0.031	54.516	0.000
		19	0.007	-0.000	54.583	0.000
		20	0.009	0.005	54.692	0.000
		21	-0.037	-0.032	56.383	0.000
		22	0.027	0.021	57.276	0.000
		23	-0.031	-0.029	58.490	0.000
		24	0.051	0.039	61.799	0.000
		25	-0.034	-0.021	63.288	0.000
		26	0.037	0.032	65.027	0.000
		27	-0.010	-0.001	65.152	0.000
		28	0.019	0.018	65.627	0.000
		29	-0.009	-0.001	65.732	0.000
		30	0.027	0.035	66.674	0.000
		31	-0.016	-0.009	66.981	0.000
		32	0.011	0.018	67.142	0.000
		33	-0.033	-0.029	68.481	0.000
		34	0.002	0.002	68.485	0.000
		35	0.036	0.031	70.149	0.000
		36	-0.006	0.010	70.193	0.001

Appendix 3:The generating process

Dependent Variable: RETURNS
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/08/23 Time: 09:54
Sample: 1/02/2019 9/20/2023
Included observations: 1231
Convergence achieved after 57 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	7.86E-05	0.000109	4.539876	0.0040
AR(1)	0.384888	0.065577	5.869209	0.0000
MA(1)	-0.613037	0.060164	-10.18947	0.0000
SIGMASQ	3.26E-05	3.99E-07	81.60861	0.0000

R-squared	0.482963	Mean dependent var	-0.001417
Adjusted R-squared	0.482963	S.D. dependent var	0.736222
S.E. of regression	0.529383	Akaike info criterion	1.566546
Sum squared resid	370.4855	Schwarz criterion	1.570467
Log likelihood	-1035.270	Hannan-Quinn criter.	1.568016
F-statistic	21.31643	Durbin-Watson stat	2.072508
Prob(F-statistic)	0.000000		
Inverted AR Roots	.38		
Inverted MA Roots	.61		

Dependent Variable: RETURNS
Method: ARMA Maximum Likelihood (OPG - BHHH)
Date: 11/08/23 Time: 10:13
Sample: 1/02/2019 9/12/2023
Included observations: 1225
Convergence achieved after 64 iterations
Coefficient covariance computed using outer product of gradients

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1.78E-06	6.64E-05	-7.56489	0.0300
MA(1)	-0.661756	0.012000	-55.14686	0.0000
SIGMASQ	3.98E-05	5.56E-07	71.62150	0.0000

R-squared	0.494449	Mean dependent var	0.000388
Adjusted R-squared	0.487779	S.D. dependent var	0.871601
S.E. of regression	0.006320	Akaike info criterion	1.881678
Sum squared resid	0.619726	Schwarz criterion	1.885599
Log likelihood	-1243.730	Hannan-Quinn criter.	1.883148
F-statistic	259.2867	Durbin-Watson stat	2.059030
Prob(F-statistic)	0.000000		
Inverted MA Roots	.66		

Appendix 4:Autocorrelation test

Correlogram of Residuals

Date: 10/25/23 Time: 17:21
Sample: 1/01/2019 9/12/2023
Included observations: 1225
Q-statistic probabilities adjusted for 1 ARMA term

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.034	0.034	1.4013	
		2	-0.036	-0.038	3.0337	0.082
		3	0.028	0.030	3.9714	0.137
		4	0.016	0.013	4.3013	0.231
		5	-0.041	-0.040	6.3727	0.173
		6	-0.043	-0.040	8.6418	0.124
		7	-0.016	-0.017	8.9563	0.176
		8	0.020	0.020	9.4474	0.222
		9	-0.021	-0.020	9.9891	0.266
		10	-0.018	-0.015	10.384	0.320
		11	0.053	0.049	13.808	0.182
		12	0.012	0.005	13.976	0.234
		13	0.012	0.017	14.156	0.291
		14	0.009	0.006	14.249	0.357
		15	0.003	-0.001	14.259	0.431
		16	0.004	0.005	14.275	0.505
		17	0.011	0.015	14.438	0.566
		18	0.027	0.030	15.362	0.569
		19	-0.038	-0.040	17.121	0.515
		20	-0.014	-0.007	17.348	0.566

Date: 10/25/23 Time: 17:17
Sample: 1/01/2019 9/20/2023
Included observations: 1231
Q-statistic probabilities adjusted for 2 ARMA terms

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.026	0.026	0.8076	
		2	0.036	0.035	2.3868	
		3	0.015	0.013	2.6624	0.103
		4	0.031	0.030	3.8833	0.143
		5	-0.021	-0.024	4.4462	0.217
		6	-0.048	-0.050	7.3594	0.118
		7	-0.004	-0.001	7.3787	0.194
		8	-0.018	-0.015	7.8033	0.253
		9	0.016	0.020	8.1137	0.323
		10	-0.029	-0.026	9.1591	0.329
		11	0.023	0.021	9.7966	0.367
		12	0.020	0.019	10.311	0.414
		13	0.019	0.016	10.781	0.462
		14	0.009	0.007	10.886	0.539
		15	0.029	0.026	11.918	0.534
		16	0.044	0.039	14.375	0.422
		17	-0.013	-0.015	14.582	0.482
		18	-0.035	-0.037	16.101	0.446
		19	-0.000	0.003	16.102	0.517
		20	0.002	0.003	16.106	0.585

Appendix 5:Heteroskedasticity test

Heteroskedasticity Test: ARCH

F-statistic	246.1831	Prob. F(1,1222)	0.0000
Obs*R-squared	205.2388	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 10/25/23 Time: 17:29
Sample (adjusted): 1/03/2019 9/12/2023
Included observations: 1224 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.53E-05	3.31E-06	7.651546	0.0000
RESID^2(-1)	0.248076	0.015811	15.69022	0.0000

R-squared	0.167679	Mean dependent var	3.52E-05
Adjusted R-squared	0.166998	S.D. dependent var	0.000124
S.E. of regression	0.000114	Akaike info criterion	-15.32779
Sum squared resid	1.57E-05	Schwarz criterion	-15.31944
Log likelihood	9382.605	Hannan-Quinn criter.	-15.32464
F-statistic	246.1831	Durbin-Watson stat	2.224670
Prob(F-statistic)	0.000000		

Heteroskedasticity Test: ARCH

F-statistic	90.89138	Prob. F(1,1228)	0.0000
Obs*R-squared	84.76543	Prob. Chi-Square(1)	0.0000

Test Equation:
Dependent Variable: RESID^2
Method: Least Squares
Date: 10/25/23 Time: 17:33
Sample (adjusted): 1/03/2019 9/20/2023
Included observations: 1230 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.41E-05	2.39E-06	10.11643	0.0000
RESID^2(-1)	0.137142	0.014385	9.533697	0.0000

R-squared	0.068915	Mean dependent var	2.86E-05
Adjusted R-squared	0.068157	S.D. dependent var	8.50E-05
S.E. of regression	8.20E-05	Akaike info criterion	-15.97703
Sum squared resid	8.27E-06	Schwarz criterion	-15.96871
Log likelihood	9827.874	Hannan-Quinn criter.	-15.97390
F-statistic	90.89138	Durbin-Watson stat	1.822808
Prob(F-statistic)	0.000000		

Appendix 6:Determining significant lags

Correlogram of Residuals Squared

Date: 10/25/23 Time: 17:37
Sample: 1/01/2019 9/12/2023
Included observations: 1225

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.248	0.248	75.567	0.000
		2	0.136	0.079	98.266	0.000
		3	0.069	0.019	104.06	0.000
		4	0.037	0.007	105.78	0.000
		5	0.019	0.001	106.20	0.000
		6	0.003	-0.007	106.22	0.000
		7	0.000	-0.002	106.22	0.000
		8	-0.003	-0.003	106.23	0.000
		9	-0.002	-0.001	106.23	0.000
		10	-0.009	-0.008	106.32	0.000
		11	0.001	0.006	106.33	0.000
		12	0.007	0.008	106.39	0.000
		13	0.009	0.006	106.51	0.000
		14	-0.006	-0.011	106.55	0.000
		15	-0.007	-0.006	106.61	0.000
		16	0.007	0.011	106.67	0.000
		17	-0.002	-0.005	106.67	0.000
		18	0.008	0.009	106.75	0.000
		19	0.006	0.003	106.79	0.000
		20	0.029	0.028	107.87	0.000
		21	0.042	0.030	110.09	0.000
		22	0.003	-0.020	110.11	0.000
		23	-0.007	-0.014	110.17	0.000
		24	0.000	0.003	110.17	0.000
		25	-0.004	-0.004	110.19	0.000
		26	0.001	0.004	110.19	0.000
		27	0.006	0.007	110.23	0.000
		28	-0.003	-0.006	110.24	0.000
		29	-0.004	-0.004	110.27	0.000
		30	-0.003	0.000	110.28	0.000
		31	-0.003	-0.002	110.29	0.000
		32	0.002	0.003	110.29	0.000
		33	-0.003	-0.005	110.31	0.000
		34	-0.001	0.001	110.31	0.000
		35	0.000	0.003	110.31	0.000
		36	0.003	0.003	110.32	0.000

Date: 10/25/23 Time: 17:39
Sample: 1/01/2019 9/20/2023
Included observations: 1231

Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.137	0.137	23.206	0.000
		2	0.029	0.011	24.256	0.000
		3	0.015	0.010	24.528	0.000
		4	0.010	0.006	24.644	0.000
		5	0.023	0.021	25.314	0.000
		6	0.006	-0.000	25.358	0.000
		7	0.007	0.006	25.424	0.001
		8	-0.002	-0.004	25.428	0.001
		9	0.004	0.004	25.444	0.003
		10	-0.004	-0.006	25.464	0.005
		11	0.001	0.002	25.466	0.008
		12	-0.004	-0.005	25.489	0.013
		13	-0.002	-0.000	25.492	0.020
		14	-0.002	-0.002	25.497	0.030
		15	-0.006	-0.005	25.537	0.043
		16	-0.000	0.001	25.537	0.061
		17	-0.004	-0.004	25.557	0.083
		18	0.006	0.007	25.600	0.109
		19	0.003	0.001	25.609	0.141
		20	-0.003	-0.003	25.620	0.179
		21	-0.008	-0.007	25.692	0.218
		22	0.001	0.003	25.693	0.265
		23	-0.006	-0.006	25.732	0.314
		24	-0.002	-0.000	25.736	0.367
		25	-0.003	-0.002	25.746	0.421
		26	-0.004	-0.003	25.768	0.476
		27	-0.000	0.001	25.768	0.532
		28	-0.012	-0.012	25.948	0.576
		29	0.001	0.004	25.950	0.628
		30	-0.003	-0.003	25.959	0.677
		31	-0.001	0.000	25.959	0.723
		32	-0.003	-0.002	25.968	0.765
		33	-0.007	-0.006	26.038	0.800
		34	-0.002	0.000	26.042	0.834
		35	0.001	0.002	26.043	0.864
		36	0.003	0.003	26.058	0.889

Appendix 7:The model estimation

Dependent Variable: RETURNS
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 11/08/23 Time: 10:32
Sample (adjusted): 1/02/2019 9/12/2023
Included observations: 1225 after adjustments
Convergence achieved after 40 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	1.91E-05	5.78E-05	3.33087	0.0407
MA(1)	-0.625796	0.019963	-31.34767	0.0000
Variance Equation				
C	1.16E-05	1.46E-06	7.971504	0.0000
RESID(-1)^2	0.229879	0.032703	7.029240	0.0000
GARCH(-1)	0.421663	0.066448	6.345740	0.0000

R-squared	0.494448	Mean dependent var	0.000388
Adjusted R-squared	0.494448	S.D. dependent var	0.871601
S.E. of regression	0.619727	Akaike info criterion	1.858621
Sum squared resid	507.7291	Schwarz criterion	1.874305
Log likelihood	-1225.478	Hannan-Quinn criter.	1.864500
Durbin-Watson stat	2.057971		
Inverted MA Roots	.63		

Dependent Variable: RETURNS
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 11/08/23 Time: 10:38
Sample (adjusted): 1/02/2019 9/20/2023
Included observations: 1231 after adjustments
Convergence achieved after 41 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)
*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	2.07E-05	7.66E-05	3.270756	0.04
AR(1)	0.312586	0.091084	3.431848	0.0006
MA(1)	-0.588964	0.071413	-8.247246	0.0000
Variance Equation				
C(4)	-1.432331	0.208805	-6.859670	0.0000
C(5)	0.357581	0.037481	9.540332	0.0000
C(6)	-0.036658	0.014035	-2.611974	0.0090
C(7)	0.890463	0.018169	49.01088	0.0000

R-squared	0.482852	Mean dependent var	-0.001417
Adjusted R-squared	0.482852	S.D. dependent var	0.736222
S.E. of regression	0.529439	Akaike info criterion	1.479361
Sum squared resid	370.5646	Schwarz criterion	1.495045
Log likelihood	-974.5973	Hannan-Quinn criter.	1.485241
Durbin-Watson stat	2.084609		
Inverted AR Roots	.31		
Inverted MA Roots	.59		

Appendix 8:Granjer Causality test

Pairwise Granger Causality Tests
Date: 10/26/23 Time: 09:07
Sample: 1/01/2019 9/12/2023
Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.
RETURNS does not Granger Cause VOLUME	1221	5.22450	0.0236
VOLUME does not Granger Cause RETURNS		1.01916	0.2460

Pairwise Granger Causality Tests
Date: 10/26/23 Time: 09:07
Sample: 1/01/2019 9/20/2023
Lags: 4

Null Hypothesis:	Obs	F-Statistic	Prob.
RETURNS does not Granger Cause VOLUME	1227	2.47625	0.0426
VOLUME does not Granger Cause RETURNS		1.09064	0.3597

Appendix 9: Volume-Return estimation

Dependent Variable: RETURNS
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 10/05/23 Time: 21:38
Sample (adjusted): 1/02/2019 9/12/2023
Included observations: 1225 after adjustments
Convergence achieved after 58 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(4) + C(5)*RESID(-1)^2 + C(6)*GARCH(-1)

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000177	0.000148	1.196654	0.0234
VOLUME	0.125990	2.32E-09	0.997402	0.1120
MA(1)	-0.621607	0.020175	-30.81012	0.0000
Variance Equation				
C	1.19E-05	1.50E-06	7.934953	0.0000
RESID(-1)^2	0.234715	0.033519	7.002412	0.0000
GARCH(-1)	0.410425	0.067920	6.042765	0.0000

R-squared	0.483587	Mean dependent var	-1.98E-05
Adjusted R-squared	0.483587	S.D. dependent var	0.736984
S.E. of regression	0.529340	Akaike info criterion	1.485914
Sum squared resid	369.5480	Schwarz criterion	1.499870
Log likelihood	-972.6884	Hannan-Quinn criter.	1.487490
Durbin-Watson stat	2.058795		
Inverted MA Roots	.62		

Dependent Variable: RETURNS
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 10/05/23 Time: 21:36
Sample (adjusted): 1/02/2019 9/20/2023
Included observations: 1231 after adjustments
Convergence achieved after 59 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(5) + C(6)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(7)*RESID(-1)/@SQRT(GARCH(-1)) + C(8)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000101	0.000167	-0.603222	0.0040
VOLUME	0.002565	3.02E-09	0.815081	0.2150
AR(1)	0.314398	0.090576	3.471077	0.0005
MA(1)	-0.590841	0.070982	-8.323775	0.0000
Variance Equation				
C(5)	-1.451343	0.213118	-6.810033	0.0000
C(6)	0.360164	0.038002	9.477397	0.0000
C(7)	-0.034327	0.015435	-2.223920	0.0262
C(8)	0.888887	0.018540	47.94540	0.0000

R-squared	0.496359	Mean dependent var	0.000102
Adjusted R-squared	0.496359	S.D. dependent var	0.875941
S.E. of regression	0.618789	Akaike info criterion	1.854694
Sum squared resid	505.8106	Schwarz criterion	1.876406
Log likelihood	-1023.273	Hannan-Quinn criter.	1.864150
Durbin-Watson stat	2.048685		
Inverted AR Roots	.31		
Inverted MA Roots	.59		

Appendix 10:Volume-Volatility estimation

Dependent Variable: RETURNS
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 10/05/23 Time: 21:39
Sample (adjusted): 1/02/2019 9/12/2023
Included observations: 1225 after adjustments
Convergence achieved after 15 iterations
Presample variance: backcast (parameter = 0.7)
GARCH = C(3) + C(4)*RESID(-1)^2 + C(5)*GARCH(-1) + C(6)*VOLUME

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-1.98E-05	0.000357	-0.055634	0.0100
MA(1)	0.050000	0.059325	0.084281	0.0000
Variance Equation				
C	5.67E-05	6.75E-07	84.03700	0.0000
RESID(-1)^2	0.150000	0.040288	3.723199	0.0002
GARCH(-1)	0.600000	0.024320	24.67146	0.0000
VOLUME	0.025600	2.74E-12	138.3218	0.0000

R-squared	0.483110	Mean dependent var	-1.98E-05
Adjusted R-squared	0.483110	S.D. dependent var	0.736334
S.E. of regression	0.529387	Akaike info criterion	1.569884
Sum squared resid	369.9312	Schwarz criterion	1.589513
Log likelihood	-1031.908	Hannan-Quinn criter.	1.557243
Durbin-Watson stat	2.073254		
Inverted MA Roots	,62		

Dependent Variable: RETURNS
Method: ML ARCH - Normal distribution (Marquardt / EViews legacy)
Date: 10/05/23 Time: 21:34
Sample (adjusted): 1/02/2019 9/20/2023
Included observations: 1231 after adjustments
Convergence achieved after 58 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(4) + C(5)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(6)*RESID(-1)/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1)) + C(8)*VOLUME

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	3.96E-05	7.93E-05	0.499945	0.0006
AR(1)	0.291175	0.094412	3.084081	0.0020
MA(1)	-0.566414	0.077280	-7.329415	0.0000
Variance Equation				
C(4)	-1.424171	0.211508	-6.733415	0.0000
C(5)	0.349172	0.039395	8.863318	0.0000
C(6)	-0.025550	0.016647	-1.534837	0.0000
C(7)	0.882763	0.019458	45.36758	0.0000
C(8)	0.002565	4.14E-07	4.044253	0.0001

R-squared	0.493986	Mean dependent var	0.003023
Adjusted R-squared	0.493986	S.D. dependent var	0.871601
S.E. of regression	0.620010	Akaike info criterion	1.758823
Sum squared resid	508.0401	Schwarz criterion	1.778429
Log likelihood	-1158.461	Hannan-Quinn criter.	1.766173
Durbin-Watson stat	2.734181		
Inverted AR Roots	.29		
Inverted MA Roots	.57		

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