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Posted Date: 27 March 2026

doi: 10.20944/preprints202603.2264.v1

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Connectedness between FX Order Flows and Exchange Rate Movements — An Empirical Analysis of Calm and Turbulent Conditions in the Ghanaian Foreign Exchange Market

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Abstract

The Ghanaian foreign exchange (FX) market has experienced substantial transformation over the past decade, marked by rising trading volumes and several episodes of exchange rate turbulence. Building on the pioneering work of Duffour et al. (2011) on order flow and exchange rate dynamics in Ghana, this study employs high-frequency daily data from 2018 to 2023—capturing both stable and volatile market conditions. Using the BK-18 spillover index, our findings show that order flows and exchange rates are tightly interconnected through bidirectional causality. Moreover, the EUR/GHS exchange rate emerges as a dominant transmitter of shocks within the multivariate system of order flows and exchange rates. These insights carry important implications for foreign exchange (FX) policy design, regulatory oversight, market monitoring, and trading strategies in Ghana.

Keywords: order flow; exchange rate; BK-18; USD/GHS; EUR/GHS

JEL Classification: A1; C1; G1

Connectedness between FX Order Flows and Exchange Rate Movements — An Empirical Analysis of Calm and Turbulent Conditions in the Ghanaian Foreign Exchange Market.

1. Introduction

Understanding the determination of currency movements through the microstructure framework is a crucial aspect of exchange rate economics. The microstructure approach examines the process and outcomes of asset exchange under trading rules (O'Hara, 1995) and theoretically and empirically demonstrates the existence of a simultaneous nexus between exchange rates and order flows (Rime, 2008). This framework is important because it takes into consideration many underlying features of the market. For instance, through order flows, exchange rate movements could be impacted by the liquidity in the FX market, individual buying and selling decisions, general market sentiment, and behavourial trends, among others. Lyons (2001) defines order flow as a metric of net buying pressure premised on the net of buyer- and seller-initiated currency transactions. Evans and Lyons (2002a) contend that the foreign exchange market is driven by currency order flows. Transaction volumes can share significant information flow with exchange rates, which is crucial for illuminating dynamic insights beyond the broad macroeconomic interaction with the currency market. As Ranaldo and Somogyi (2021) alluded to, determining security prices in financial economics remains an essential question.

This study seeks to explore the relationship between order flows and three currency pairs in the Ghanaian FX market. Inspired by Duffour et al. (2011), recent developments have led to pressing gaps in the extant literature. For example, the study by Duffour et al. (2011) examined trades by five large commercial banks in Ghana, which were estimated to account for 80% of the market, focusing on the

U.S. dollar/Ghanaian cedi (USD/GHS) currency pair. However, this study resorts to expanded data covering the entire Ghanaian interbank FX market. Essentially, we approach this empirical work from a multivariate perspective, extending the study beyond the USD/GHS to cover other currency pairs, such as the euro/Ghanaian cedi (EUR/GHS) and Great British pound/Ghanaian cedi (GBP/GHS). Although the EUR/GHS and GBP/GHS constitute less than 20 per cent of the market trading volume, we cannot discount the shock transmission mechanism from these minority currency pairs.

Given that Ghana experienced a foreign exchange crisis in 2022, which spilt over into 2023, the analysis was based on calm (2018-2021) and turbulent (2022-2023) market conditions. In addition, a network of all order flows and currency pairs was built to gauge the shock transmission dynamics among the variables in the system.

Several studies in Ghana have covered the interactions between exchange rate movements and the macroeconomy (see Antwi et al., 2020; Arthur and Addai, 2022), commodities (see Archer et al., 2022; Barson et al., 2023), and the stock market (Agyei et al., 2022; Atipaga et al., 2024). Despite the argument of Evans and Lyons (2002) on the momentous pricing power of order flows, the extant literature on the Ghanaian FX market lacks significant and recent insights. These insights are imperative in the current FX dispensation after frequent exchange rate pressures in the Ghanaian FX market. The significance of these insights is further accentuated by the assertion of some researchers that the macroeconomic prediction of currency trends is deficient (Anifowose et al., 2018). Evans and Lyons (2001) also noted that two-thirds of the impact of macro developments on the exchange rate is conveyed through order flow. Hoosain et al. (2017) argued that the failure of macroeconomic models to predict exchange rate direction in the short term has activated the need to resort to models that can explain price movements in the short term, such as the microstructure approach.

The study is grounded in the FX microstructure framework, which posits that exchange rate movements are influenced not only by macroeconomic fundamentals but also by trading behaviours and information embedded in order flows. Order flow acts as a conduit for both liquidity imbalances and informational signals, contributing to short-term (transitory) as well as long-lasting (permanent) shifts in exchange rates.

Under calm (stable) market conditions—characterized by sufficient liquidity and low uncertainty—the influence of order flow on exchange rates is expected to be temporary. However, during periods of market stress or turbulence, sharp currency fluctuations tend to occur, and the impact of order flow becomes more persistent, exerting a stronger and more enduring effect on exchange rate dynamics.

FX order flow provides crucial insight into exchange rate dynamics, capturing short-term market pressures and information that macroeconomic fundamentals alone cannot fully explain. This is supported by Evans and Lyons (2002a), who explained that a significant portion of exchange rate variation at high frequency could be explained by order flows. Because order flow aggregates transactions from corporate clients, foreign portfolio investors, and central bank interventions or intermediation, it captures a broad spectrum of market intentions and informational signals—positioning it as a highly relevant and forward-looking indicator of exchange rate movements.

The Ghanaian cedi has been one of the most buffeted currencies in the world in the past few years. According to Bank of Ghana data, in 2022, the Ghanaian local unit ended the year with a cumulative depreciation of 30%, 22%, and 25% against the USD, GBP, and EUR, respectively. The October 2022 performance highlighted the crisis as the Ghanaian currency depreciated by over 40% against all three major currencies. Likewise, in 2023, the Ghanaian cedi ended the year with a cumulative depreciation of 28%, 32%, and 30% against the USD, GBP, and EUR, respectively. Meanwhile, these volatilities have coincided with a surge in FX trading volumes over the years, warranting the empirical nexus between these key variables. This study is significant for an inflation-targeting monetary policy regime in Ghana, where a depreciating exchange rate could be a source of risk to achieving the inflation target.

The findings from the study make several contributions to literature. Firstly, the microstructure framework for order flow and exchange rates has dominantly been unidirectional, i.e. the effect of order flow on exchange rate. However, it is possible that the direction of a currency pair can equally drive trading behaviour. Therefore, this study attempts to fill the gap by examining the extent to which order flows and the currency pairs drive each other in the Ghanaian FX market (bivariate). We believe these insights are important in trying to unravel the dynamic relationship between FX order flows and exchange rates.

This study also makes important empirical contributions to literature. Much of the foundational FX microstructure research has concentrated on advanced, highly liquid markets, leaving relatively less evidence from emerging or frontier economies. Consequently, this study is well positioned to provide novel insights from an African market that is comparatively shallow and, in certain respects, fragmented. African FX markets are widely characterized by lower liquidity, greater segmentation, and structural frictions, thereby making recent empirical evidence particularly valuable. The use of up-to-date data in this study therefore offers a more nuanced and contextually relevant contribution to literature.

The study's contribution is further enhanced by its segregation of observations into calm and turbulent market regimes. This regime-specific perspective allows for a deeper understanding of market behaviour that cannot be captured through a uniform analytical approach. Evidence from this distinction points to a fundamentally non-linear relationship between the variables of interest, underscoring the appropriateness of adopting an empirical methodology designed to accommodate such non-linearity.

By employing the BK-18 spillover/connectedness index to estimate the relationship between order flow and exchange rates in Ghana. Connectedness among variables could be linked to TVP-VAR, which is popular for analysing the dynamic behaviour of variables by allowing coefficients to vary over time (Lubik and Matthes, 2015). It goes beyond a standard VAR model, which explains the evolution of variables through their lags by treating the coefficients as stochastic processes. It also allows the coefficients to vary in response to shocks and other market trends over time (Balli et al., 2021). Diebold Yilmaz (2012) (DY-12) proposed a volatility spillover (connectedness) measure using the generalized forecast error variance decomposition. We employed the Barunik and Krehlik (2018) (BK-18) spillover index, an extension of the DY-12 spillover index. According to Bossman et al. (2022), the BK-18 model is based on heterogeneous shock responses. This is suitable for a study where market homogeneity is not the norm.

Order Flow as a Function of Ghana's Interbank FX Market

A total of 23 banks operate in the Ghanaian interbank FX market since August 2017, after a restructuring programme in the banking sector, which eventually led to a downsizing. These banks are classified as universal banks in Ghana. Together with forex bureau (cash/spot market), they are the only institutions that are officially allowed to buy and sell forex under the current licensing regime of the Bank of Ghana. The banking space is shared between domestic and foreign banks. 40 per cent of the banks are indigenous. This is indicative of the fact that the banking landscape in Ghana is dominated by foreign banks. Unlike the forex bureaux segment of the market, which is designed as a retail market, all big-ticket transactions go through the interbank market. This is because of the clientele pool they are exposed to, such as mining, oil, construction companies, and other large corporations. In addition to that, the forex receipts of remittance flows are currently ceded to the banking sector. The central bank's forex intermediation/interventions go through the banking system directly. The banking sector also controls over 80 per cent of the forex trading volumes in Ghana, buoyed by interbank trades. Each bank submits its purchases and sales data to the Bank of Ghana daily to form the aggregate data hub. From the perspective of the banks, net buying pressures mean the aggregate sales to banks by their customers outweigh purchases. Conversely, net selling pressure is an indication of more purchases from banks by their customers.

The net order flow position is constructed as:

$$Order\ Flow = \frac{Purchases - Sales}{Purchases + Sales} \tag{1}$$

Therefore, a positive number represents net purchases, while a negative number represents net sales. In simple terms, a net purchase represents improved liquidity for the banks, while a net sale means a decline in liquidity.

Figure 1.1 shows that USD/GHS purchases and sales have had a significant share of the FX trading volume in Ghana.

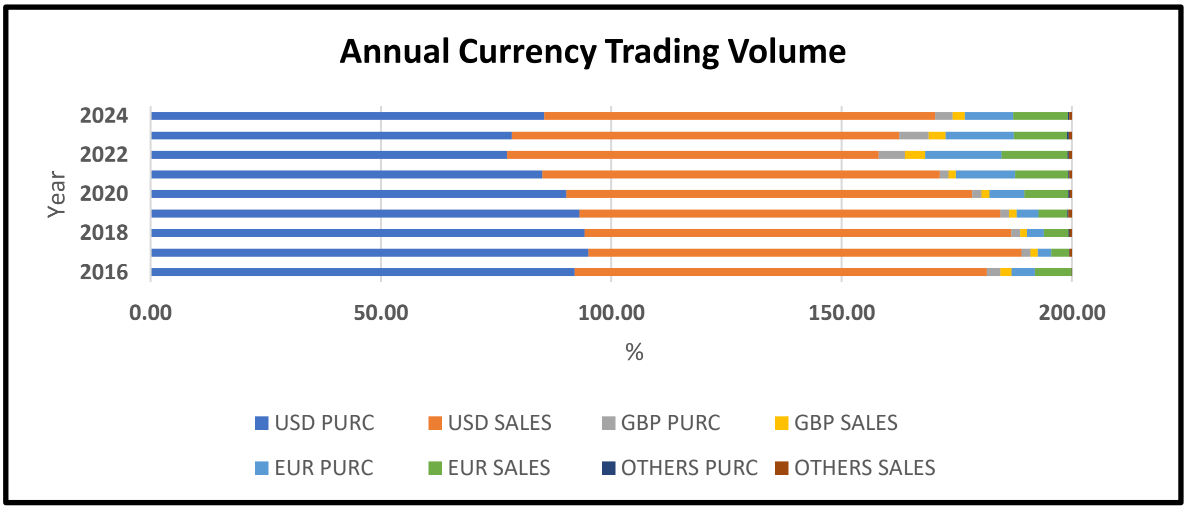

Figure 1.1. Yearly Trading Volume of Banks in Ghana's FX Market. Source: Author's construct from Bank of Ghana Data.

This chapter sought to bring to light the need to empirically investigate the connectedness between order flows and exchange rates in Ghana. The study improves on the foundational work by Duffour et al. (2011) to appreciate the drivers of Ghana's currency volatility within the microstructure framework using the BK-18 spillover index. The rest of the thesis is structured as follows: In Chapter 2, some theoretical and empirical studies are reported to understand the evolution of this topic and the current gaps in the extant literature. Chapter 3 covers the properties of the data and methodology. In Chapter 4, we present the results of the BK-18 spillover index and their implications within the context of the FX market in Ghana. The study concludes in Chapter 5 with accompanying proffered recommendations.

2. Analysis of Related Body of Knowledge

The microstructure analysis of order flows and exchange rates remains an important branch of exchange rate economics. Past studies have been primarily centred on developed and a few emerging markets, owing to systems that can produce live and high-frequency data. The live and high-frequency data convey significant information content. However, the lack of readily available data has led to minimal coverage in frontier markets. The available data in this space is mostly aggregated daily or weekly and is only available to central banks. Due to the numerous traders on both the buying and selling sides who act on information from different angles, we can infer market behaviours linked to the heterogeneous market hypothesis (HMH) and the adaptive market hypothesis (AMH), both of which are extensions of the well-known efficient market hypothesis (EMH). These theories explain the importance of information in asset pricing. Melvin and Xixi (2000) opined that information is a pivotal determinant of asset prices in both the theoretical and empirical frameworks.

The HMH (Muller et al., 1993) proposes a non-homogeneous market behaviour. This means market participants treat the same information differently based on a range of factors, including risk appetite, profit motives, and trading orientation, among others. Agyei et al. (2022b) stated that through the analysis of past and current events, market players build their investment strategies over varied time scales according to their risk and return inclinations. Empirically, Chin et al. (2013) tested and confirmed the properties of the HMH in financial markets. Singh (2022) highlighted that a crucial factor in explaining exchange rate volatility is investor heterogeneity. The HMH posits non-linearity in trading behaviours, relative to the assumption of a linear pattern under the EMH.

The AMH (Lo, 2004) also deviates from the EMH (Fama, 1970). It explains the relationship between rationality and irrationality in the market, based on market evolution and behavioural finance. Noreen et al. (2022) carried out a study on the NYSE and concluded that investors displayed properties of the AMH through myopic and non-myopic attributes concerning losses, indicating both the efficiency and inefficiency of the market at different time scales.

In the 1970s, several models aimed at determining exchange rate movements emerged. For instance, Frankel (1979) proposed a monetary approach, Dornbusch (1976) suggested a sticky-price monetary model, and Kouri (1976) propounded the portfolio balance approach. A popular theory within the context of order flows and exchange rate movements is the market microstructure theory. This concept was born in 1976 by Mark Garman and focused on moment-to-moment trading activities in asset markets. The market microstructure theory is an established framework and a branch of financial economics that explains the determination of prices through trading volumes. While asset trading is a dominant focus area of financial economics, market microstructure delves into the correlation between trading mechanisms and their outcome, with the ultimate objective being the appreciation of the behaviour of financial markets and associated intermediaries (Doostian and Touski, 2024).

Among the proponents of this framework are Evans and Lyons (2002a), who suggested a microstructure model that incorporates public macroeconomics and the heterogeneous information of private agents, where order flow is mapped for price discovery. This theory encompasses the reaction of market players, information flow, liquidity, and how these factors combine to drive exchange rate volatility. Kissel (2014) posited that market microstructure focuses on trading volumes, the price discovery process, spreads and quotes, trading behaviour, and transaction costs.

Several FX microstructure frameworks exist. This includes Kyle (1985) and Evans and Lyons (2002a). Kyle (1985) explored optimal trading when an informed investor's trades influence prices. The problem an informed trader must contend with is the propensity for prices to move against him if he trades aggressively based on the information available. For example, if the trader buys aggressively, the asset's price will increase and vice versa. The model described two versions: a static model with one trading period and a complex model with a sequence of trading periods.

Meanwhile, the one proposed by Evans and Lyons (2002a) was centred on exchange rate movements premised on order flows. Other aspects to glean from the model are the information content conveyed by net order flow and market efficiency. The model was motivated by the findings of Frankel and Rosen (1995) and Meese (1990), which indicated that exchange rate movements at short-term horizons up to a year cannot be explained by macroeconomic variables. This model has contributed significantly to the market microstructure literature due to its practical relevance.

Empirically, earlier arguments by Cai et al. (1998) suggested that most exchange rate volatility at the short to medium horizons relates to order flow and not macroeconomic variables. This is what heralded the interest in microstructure studies (FX order flows) in the determination of exchange rate movements. As previously mentioned, most of these studies have been conducted in developed markets or emerging economies that have readily available data or very liquid markets. For example, Kleinbord and Li (2017) carried out a study involving some G-10 currency pairs (USD/AUD, USD/CAD, USD/EUR, USD/GBP, and USD/JPY). The crux of the study was to determine the effects of order flows on the above-mentioned currencies after employing univariate and multivariate models. The authors found that order flows had a significant negative relationship with exchange rates during periods of tranquillity but became significantly positive during turbulent periods. The conclusion from this research work points to aggressive trading and falling currencies in times of raucous market conditions. This is particularly insightful, especially in this current dispensation of global shocks.

Duffuor et al. (2011) examined exchange rate and order flow dynamics in Ghana using a VAR model. The study was carried out with full sample data (January 2000 to December 2007) and segmented data – crisis (January 2000 to December 2000) and stable (March 2002 to December 2007). Like Kleinbord and Li (2017), it was found that during the crisis period, when the market was almost illiquid, order flow had a relatively larger impact on exchange rates than in the more stable, less illiquid period. Further angles explored by the authors revealed that the unexpected component of order flow had a positive and long-lived effect on the banking sector exchange rate compared to the unofficial (proxy for black market) exchange rate in both stable and crisis periods.

Equal reference can be made to Koosakul and Ananchotikul's (2018) study on the Thai market from January 2012 to December 2016 using the Generalized Methods of Moments (GMM) estimates. The data was classified into resident and non-resident order flows to determine which one held more influence over the movements of the Thai Baht. Several findings were uncovered. Firstly, non-resident order flows had an important influence on the movement of the Thai Baht compared to resident order flows. Secondly, fundamentals and the Thai exchange rate drove non-resident order flows, indicating a bicausality between trading volumes and currency movements. It was also observed that resident players behaved as contrarians by buying the Thai Baht when it depreciated.

Related to this trend is the finding by Phiri et al. (2023), whose work in Zambia covered the period 2016 to 2020. Despite order flows broken into customer types, the authors, after employing a VAR model, generally concluded that the exchange rates in the Zambian FX market were largely driven by order flows.

The properties of the heterogeneous market hypothesis can be inferred from the approach of Duffour et al. (2011), Koosakul and Ananchotikul (2018), and Phiri et al. (2023). Similarly, Ronaldo and Somogyi (2021) reported that global order flows impacted spot prices heterogeneously across agents, time, and currency pairs. The study generally concluded that some agents were more informed than others. For instance, corporates and banks were significantly driven by their lagged flows, with the strong autocorrelation supporting the idea that sophisticated agents had superior access to information in the FX market. An interesting observation is the fact that the segmented customer and market studies have largely pointed to order flows significantly driving currency movements. Even in the world's largest OTC market with many currency pairs (15), Menkhoff et al. (2016) noted that order flows were highly informative about future exchange rates after investigating a cross-section of customers. This study effectively signalled that order flows had a predictive power on exchange rate movements.

Hoosain et al. (2017) resorted to a hybrid approach by combining both microeconomic and macroeconomic factors using a VAR model in the South African market for the period January 2004 to December 2016. The authors sought to ascertain how the micro and macro variables drive the movements of the USD/ZAR. The study found that the USD/ZAR movement is explained by order flow in the short run and long run, but the macro fundamentals only drove the South African currency in the long run.

Anifowose et al. (2018) found that order flows in the Malaysian FX market explained a significant portion of the movements of the USD/MYR, employing a VAR model for high-frequency data with a 15-minute frequency from January 2010 to December 2015.

A significant observation from the above literature points to the predictive and influential power of order flow on exchange rate movements. While the literature has adequately covered analysis of segmented markets or customers, little attention has been given to relationships during highly volatile and calm market conditions. It is also interesting to note that VAR models have been dominantly employed for this study across different markets.

Based on observations, this study makes several contributions to literature. Empirically, we adopt the BK-18 spillover index, which extends the Diebold-Yilmaz (2012) spillover approach to the frequency domain. This approach offers a nuanced analysis of the nexus between exchange rates and order flows in Ghana, as the time-frequency angle makes it possible to appreciate whether shocks are

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temporary or permanent. We also fill a significant gap in the exchange rate literature in Ghana, and by extension, Africa, as the microstructure approach has been thinly researched.

3. Data and Methodology

This chapter delves into the features of the data, trends, and sources. The characteristics of the data can help in appreciating the choice of methods for this study. Additionally, the chapter also explains the methodological tools employed to examine the relationship between order flow and exchange rates in calm and turbulent market conditions in Ghana. The first set of data to analyse is the bivariate relationship between order flows and exchange rates across three currency pairs – USD/GHS, EUR/GHS, and GBP/GHS. Each is classified into calm and turbulent market conditions.

Table 3.1. Descriptive Statistics of Order Flow and Exchange Rate Data in Calm and Turbulent Market Conditions.

	USDGHS_Calm		USDGHS_Turbulent		EURGHS_Calm		EURGHS_Turbulent		GBPGHS_Calm		GBPGHS_Turbulent	
	Exchange Rate	Order Flow	Exchange Rate	Order Flow	Exchange Rate	Order Flow	Exchange Rate	Order Flow	Exchange Rate	Order Flow	Exchange Rate	Order Flow
Mean	0.000	0.008	0.001	-0.033	0.000	-0.090	0.001	0.093	0.000	0.056	0.001	0.180
Variance	0.000	0.016	0.000	0.020	0.000	0.071	0.000	0.058	0.000	0.066	0.000	0.057
Skewness	0.366	1.069	-2.267	-2.731	-0.020	0.103	-1.558	-0.234	0.176	-0.325	-1.794	-0.326
Kurtosis	5.586	16.577	33.781	21.833	34.250	-0.086	26.859	0.765	5.413	-0.195	27.313	0.293
Jarque Bera	1308.080	11512.079	23911.252	10425.508	483.091	2.055	15048.575	16.575	112.697	18.891	15619.771	10.487
Counts	990	990	495	495	989	989	495	495	990	990	495	495

Source: Author's Construct [1]Calm market conditions span January 2018 to December 2021, while [2]turbulent market conditions cover January 2022 to December 2023. The data is a full representation of the total forex purchases and sales of the interbank market in Ghana. From the position of the aggregate data of the banks, a net purchase represents an inflow, and a net sale is an outflow. A few banks dominate forex trades in Ghana, owing to their clientele base from both on-shore and offshore sources. This order flow data is currently the best option from Ghana, making it suitable for appropriate results and policy recommendations. The choice of daily frequency allows us to fully grasp the trends from a closer and granular angle, as exchange rate data mostly reflects current underlying trends and forecast information in real time. While the order flow data was calculated as (purchases – sales)/ purchases + sales, the exchange rate data was transformed into returns as presented in equation 2. The data is only available on working days in Ghana, meaning holidays and weekends are not factored into the trading days.

$$r_t = \left(\frac{P_t}{P_{t-1}}\right) - 1 \qquad (2)$$

Where r_t = returns at time t. P_t and P_{t-1} represent current prices and period-lagged prices.

[1] Market conditions where exchange rate volatility is relatively calm

[2] Market conditions where the forex market is volatile/period of extreme currency depreciation

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To justify the classification of the data into calm and turbulent market conditions, we refer to Figure 3.1, which shows a 30-day rolling mean and volatility graph from 2018 to 2023. The graph shows relative stability from 2018 to 2021, followed by a spike from 2022 to 2023. A similar trend is observed for the EUR/GHS and GBP/GHS (see appendices 1 and 2).

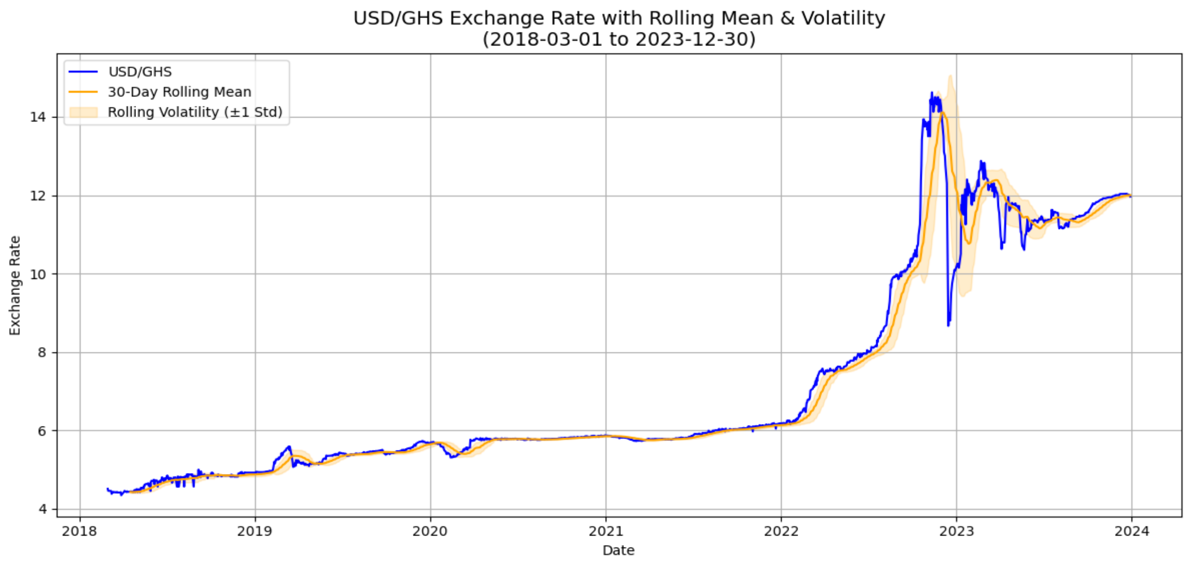


Figure 3.1. 30-Day Rolling and Volatility of the Nominal USD/GHS Exchange Rate. *Source: Author's Construct from Bloomberg Data.*

From Table 3.1, it is observed from the variance that the order flow variables are generally more volatile than the exchange rates. The EUR/GHS and GBP/GHS order flows are more volatile than the USD/GHS. Therefore, the decision to include these 'minority' order flow data in the Ghanaian FX market is justified. Despite being thinly traded compared to the USD/GHS trading volumes, they could possess potential shock transmission power. Skewness measures the asymmetry of the data distribution. When it is greater than zero, it means the right tails of the distribution are fatter than the left. The same intuition applies to a situation when the skewness is less than zero. The USD/GHS order flow in turbulent times posted the highest skewness with negative asymmetry.

Kurtosis, on the other hand, measures the tailedness of the data relative to the mean. A normal distribution possesses a kurtosis of 3 (mesokurtic). A kurtosis measure over 3 represents heavy tails relative to the normal distribution (leptokurtic). When the kurtosis has a measure less than 3, it has lighter tails compared to the normal distribution (platykurtic). Generally, most of the variables exhibit fat tails apart from the EUR/GHS and GBP/GHS order flow in both calm and turbulent market conditions. The broad non-normality of the data is also confirmed by the Jarque-Bera test, which combines both skewness and kurtosis

The data was derived from a combination of sources: Bloomberg and the Bank of Ghana. All licensed universal banks send their forex trading data to the Financial Markets Department of the Bank of Ghana daily. Bloomberg, on the other hand, relies on currency pricing data submitted by contributors such as banks and FX brokers daily to determine the USD/GHS, EUR/GHS, and GBP/GHS exchange rates. The closing price at the end of a trading day becomes the rate for that specific date. This means that the data being employed for the study are derived from a cumulative position. Table 3.2 below summarises the variables and sources of data.

 doi:10.20944/preprints202603.2264.v1

Table 3.2. Data Sources.

Variables	Source
USDGHS Order Flow	Financial Markets Department, Bank of Ghana
EURGHS Order Flow	Financial Markets Department, Bank of Ghana
GBPGHS Order Flow	Financial Markets Department, Bank of Ghana
USDGHS Rate	Bloomberg
EURGHS Rate	Bloomberg
GBPGHS Rate	Bloomberg

Source: Author's Construct from Bloomberg and Bank of Ghana Data.

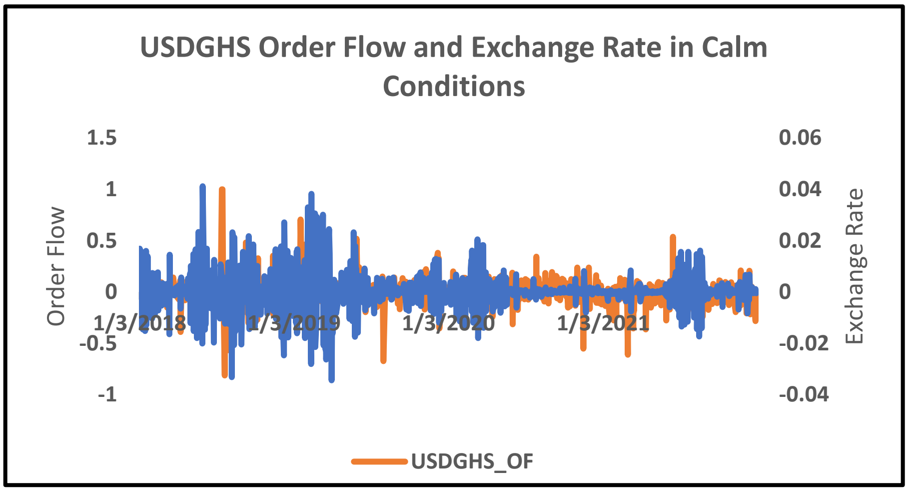
Another step in the data analysis is the combination of all order flow data and exchange rates to determine the transmission of shocks among the variables. Therefore, the descriptive statistics of all three currency pairs and their corresponding order flows are presented in Table 3.3. This analysis is carried out over full data coverage from January 2018 to December 2023. The statistical features of the order flow and exchange rate data are like those captured in Table 3.1, where the data are disaggregated into calm and turbulent market conditions. From the variance results, the order flow data across all the currency pairs is more volatile relative to the exchange rates. All the order flow and exchange rate variables are negatively skewed. Apart from the EUR/GHS and GBP/GHS data, which have thinner tails, the remaining order flow and exchange rate variables are leptokurtic, indicating the dominance of fat tails. This aligns with the results of the Jarque-Bera tests, which confirm broad non-normality in the data distribution.

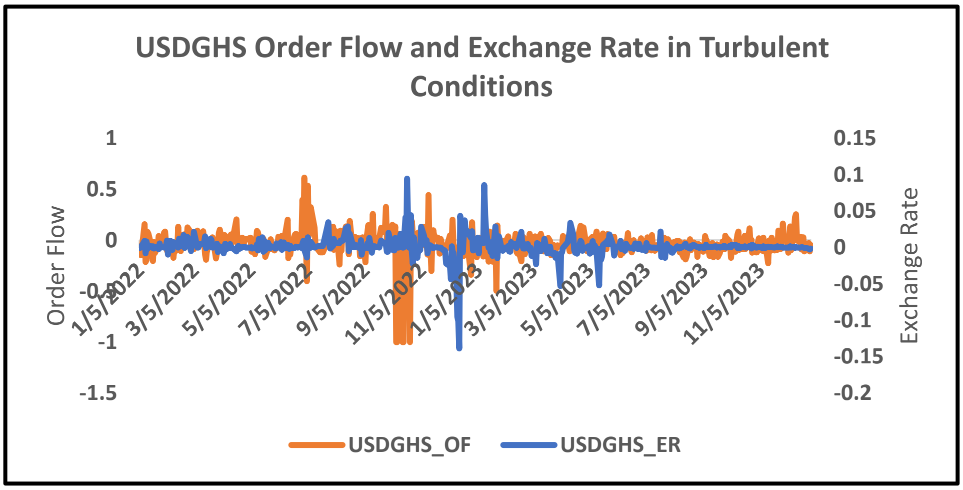
Table 3.3. Descriptive Statistics of Order Flow and Exchange Rate over Full Data.

	USDGHS_ ER	USDGHS_ OF	EURGHS_ ER	EURGHS_ OF	GBPGHS_ ER	GBPGHS_ OF
Mean	0.001	-0.005	0.001	-0.029	0.001	0.097
Variance	0.000	0.018	0.000	0.074	0.000	0.066
Skewness	-1.944	-0.558	-1.329	-0.044	-1.302	-0.034
Kurtosis	46.926	19.611	35.911	-0.079	28.275	-0.034
Jarque Bera	13.710	23856.998	80179.056	0.862	49853.622	27.987
Observations	1485	1485	1485	1485	1485	1485

Source: Author's Construct from Bloomberg and Bank of Ghana.

The broad non-linearity of the data is a key motivation for the adoption of the BK-18 spillover index technique. In Figure 3.2, the transformed data are presented in line graphs for visual appreciation. The graphs confirm the volatility clusters in the distribution of the data.


USDGHS Order Flow and Exchange Rate in Calm Conditions
Order Flow
Exchange Rate
1.5
1
0.5
0
-0.5
-1
0.06
0.04
0.02
0
-0.02
-0.04
1/3/2018
1/3/2019
1/3/2020
1/3/2021
USDGHS_OF


USDGHS Order Flow and Exchange Rate in Turbulent Conditions
Order Flow
Exchange Rate
1
0.5
0
-0.5
-1
-1.5
0.15
0.1
0.05
0
-0.05
-0.1
-0.15
-0.2
1/5/2022
3/5/2022
5/5/2022
7/5/2022
9/5/2022
11/5/2022
1/5/2023
3/5/2023
5/5/2023
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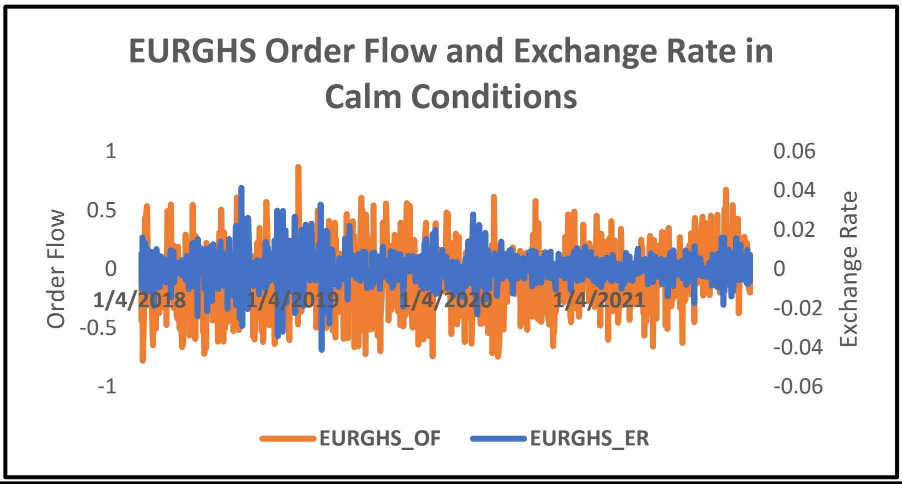

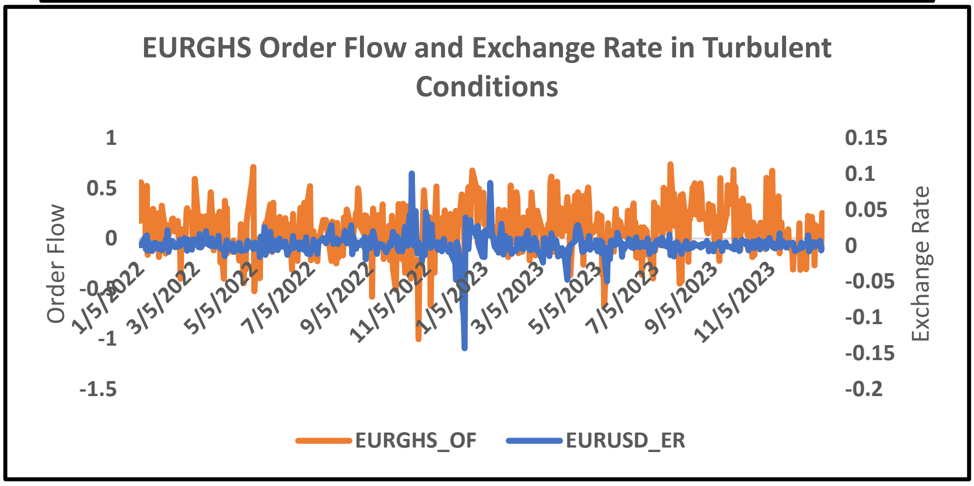

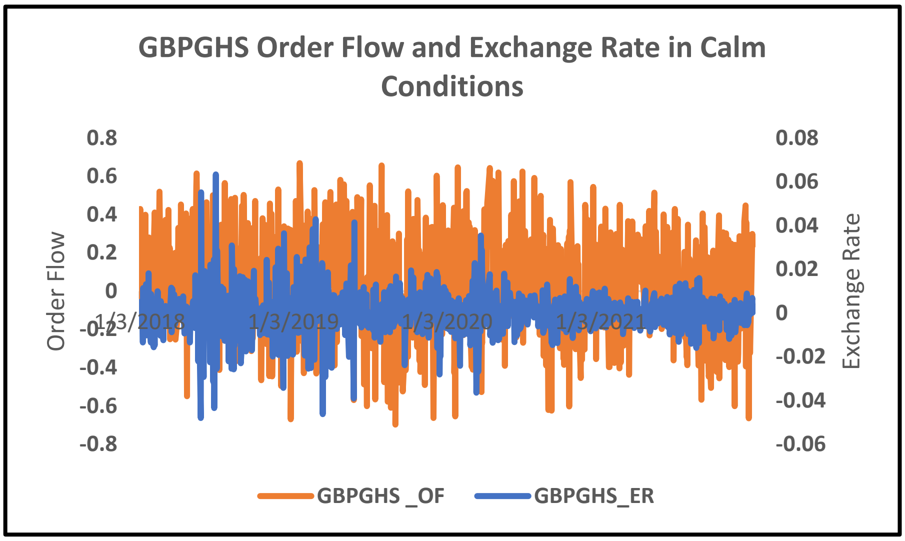

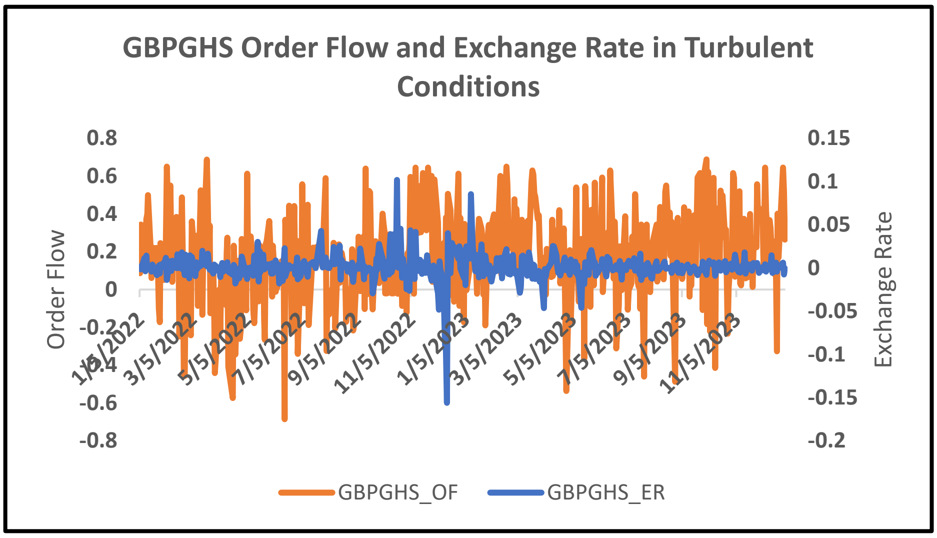

[3]**Figure 3.2.** Transformed Versions of Data for Empirical Analysis. ***Source: Author's Construct from Bloomberg Data.***

Research Design

In this section, we present methodological techniques to accomplish the research objectives.

The BK-18 Spillover/Connectedness Index

The BK-18 spillover index is associated with connectedness and network spillovers among macro-financial variables. The foremost unique attribute of the BK-18 spillover is its ability to decompose the connectedness and spillovers in the time-frequency domain. Connectedness among variables can be traced to TVP-VAR, which is known for its stochastic volatility and adjusts for time-varying variances in the error process that affects the VAR (Lubik and Matthes, 2015). For starters, a vector autoregressive (VAR) model can be described in simple terms as a time series model that explains the evolution of variables dependent on their lags. TVP-VAR, by extension, builds on this strand to model coefficients as a stochastic process.

Connectedness refers to how spillovers from other variables account for the forecast error variance in the system. Connectedness has a property of time evolution; therefore, it captures

[3] USDGHS_OF = USDGHS Order Flow USDGHS_ER = USDGHS Exchange Rate. The ER (exchange rate) and OF (order flow) definitions apply to all pages.

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different dispensations such as crises and regime shifts, among others. Inspired by Diebold and Yilmaz (2012) (DY-12), the Barunik and Krehlik (2018) (BK-18) spillover index has been employed for this study. This adopts the generalised forecast error variance (GFEVDs) to estimate the connectivity. The data is decomposed with the matrix of a VAR model. Subsequently, we construct an expression represented by the K-variate procedure, $Y_t = (y_{1,t,....,} y_{k,t})'$ given that $t = 1, ..., T$ and VAR (ρ) which may be captured as:

$$Y_t = \sum_{i=1}^{p} \omega_i \, y_{t-i} + \mu_t \quad (3)$$

ω_i and μ_t represent coefficient and white noise covariance matrix $\prod$ respectively. A regression is later run between each of the variables in (3) with its own ρ lags and the ρ lags of all the remaining variables. It is imperative to work with $(K \times K)$ matrix lag-polynomial $(I_K - \emptyset_1 L - _{...} - \emptyset_P L^P)$ with identity I_K. Bossman et al. (2022) argued that the VAR system is characterized by a moving average MA (∞) when the roots of the representative operation $|\theta(z)|$ is outside the unit circle.

$$Y_t = \Psi(L)\mu_t \quad (4)$$

From (4) above, $\Psi(L)$ denotes an infinitely lagged polynomial. As long as $\Psi(L)$ contains an infinite number of lags, it needs to be approximated with moving average coefficients Ψ_h calculated at h = 1,…, H horizons. According to Barunik and Krehlik (2018), a shock to a variable within the system does not appear alone; therefore, an identification scheme is an important step in the calculation of variance decomposition. It is important to note that a standard approach that relies on Cholesky factorisation depends on the ordering of the variables, which could complicate the measures. Pesaran and Shin (1998) proposed a generalised identification that produces variance decomposition invariant ordering. The kth variable, otherwise referred to as GFEVD, impacts the variance of the forecast error of the element j and can be constructed as:

$$(\Theta_H)_{j,k} = \frac{\sigma_{k,k}^{-1} \Sigma_{h=0}^{H} \Psi_h \Pi)(\Psi_h \Pi)\,(\Psi_h \Pi)_{j,k})^2}{\Sigma_{h=0}^{H} (\Psi_h \, \Pi_{h}{}')_{j,k}} \quad (5)$$

From Equation (5) above, Ψ_h is a (K x K) matrix of moving average coefficients at lag h and $\sigma_{kk} = (\Sigma)_{k,k.}$ $(\Theta_H)_{j,k}$, on the other hand, is a representation of the kth variable's contribution to the variance of the forecast error of the element j, at horizon h. Since the rows of the variance decomposition matrix do not aggregate to one, a standardization of the matrix Θ_H is generated in Equation (6) below, in line with completeness.

$$\left(\widetilde{\Theta}_H\right)_{j,k} = \frac{(\Theta_H)_{j,k}}{\Sigma_{k=1}^{N} (\Theta_H)_{j,k}} \quad (6)$$

$\Sigma_{j=1}^{N} \left(\widetilde{\Theta}_H\right)_{j,k}$ is now equal to one while the aggregation of all elements in $\widetilde{\Theta}_H$ is equal to K. The overall connectedness could be aggregated from the pairwise connectivity in Equation (6) above. Following Diebold and Yilmaz (2012), this can be regarded as a proportion of variation in predictions provided by errors other than own error as captured in Equation (7) below.

$$C_H = 100 * \frac{\Sigma_{j \neq k} (\widetilde{\Theta}_H)_{j,k}}{\Sigma \widetilde{\Theta}_H} = 100 * \left(1 - \frac{Tr\{\widetilde{\Theta}_H\}}{\Sigma \widetilde{\Theta}_H}\right), \quad (7)$$

$Tr\{.\}$ serves as the trace operator. Meanwhile, the summation of all elements in the matrix denotes the denominator. In this regard, connectedness can be described as the forecast variance's relative contribution to the other variables in the system. On the back of this, we can infer bi-directional connectivity as "to" and/or "from" market i from all other markets k (Bossman et al., 2022). To arrive at net connectivity, we consider the difference between the spillovers "to" and "from." When a market records a positive net spillover, it is seen as a net transmitter, while a negative spillover is described as a net recipient of shocks.

Another dimension to this model is the extraction of frequency dynamics as short-, medium-, and long-term connectedness. This is considered through the spectral representation of variance decomposition dependent on frequency responses to shocks rather than shocks from impulse responses. To build on this intuition, a frequency response function $\Psi(e^{-i\omega}) = \sum_h e^{i\omega h} \Psi_h$ can be constructed. This is extracted as a Fourier transform of the coefficients Ψ_h, with $i = \sqrt{-1}$. A moving average MA (∞) is achieved through a spectral density of Y_t at frequency ω.

$$S_{y(\omega)} = \sum_{h=-\infty}^{\infty} E(Y' \, Y_{t-h})e^{-i\omega h} = \Psi(e^{-i\omega})\, \Pi\Psi'(e^{+i\omega}). \quad (8)$$

From Equation (8), $S_{y(\omega)}$ denotes the power spectrum, which explains the distribution of the variance Y_t over the frequency components of ω. In Equation (9), $\omega \in (-\pi, \pi)$ delineates the causation spectrum. This reflects representative of shocks in the kth variable at a frequency ω.

$$\left(\mathfrak{F}(\omega)\right)_{j,k} = \frac{\sigma_{kk}^{-1}\left|\Psi(e^{-i\omega})\Pi_{j,k}\right|^2}{\left(\Psi(e^{-i\omega})\Pi\Psi'(e^{+i\omega})\right)_{j,j}} \quad (9)$$

The denominator provides an avenue for equation (9) to be regarded as within-frequency causation. To arrive at a natural decomposition of GFEVD to frequencies, $\left(\mathfrak{F}(\omega)\right)_{j,k}$ is weighed by the frequency share of the variance of the jth variable. The weighting function is therefore defined as:

$$\Gamma_j = \frac{(\Psi(e^{-i\omega})\Pi\Psi'(e^{+i\omega}))_{j,j}}{\frac{1}{2\pi}\int_{-\pi}^{\pi}(\Psi(e^{-i\lambda})\Pi\Psi'(e^{+i\lambda}))_{j,j}\, d\lambda} \quad (10)$$

This is a representation of the power of the jth variable at a given frequency, which aggregates through frequencies to a constant value of 2π. Given that the Fourier transform of the impulse response is a matter of complexity, the generalized causation spectrum is the squared modulus of the weighted complex numbers, which produces a real quantity. Instead of measuring connectedness at single frequencies, the ideal situation is to consider it over bands. A formal representation of the frequency band d is given as d = (a, b): a, b $\in (-\pi, \pi)$, a < b, for which the GFEVD is defined as Equation (11) below.

$$(\Theta_d)_{j,k} = \frac{1}{2\pi}\int_a^b \Gamma_j\,(\omega)\left(\mathfrak{F}(\omega)\right)_{j,k} d\omega. \quad (11)$$

We can construct a scaled generalized variance decomposition in the same frequency band d as

$$\left(\widetilde{\Theta}_d\right)_{j,k} = \frac{(\Theta_d)_{j,k}}{\sum_k (\Theta_d)_{j,k}} \quad (12)$$

The within-frequency and frequency connectivity across d are contained in Equations (13) and (14), respectively.

$$C_d^W = 100.\left(1 - \frac{Tr\{\widetilde{\Theta}_d\}}{\sum \widetilde{\Theta}_d}\right) \quad (13)$$

C_d^W denotes the connectivity that appears inside a frequency band and is weighted by the series' power on that band. Meanwhile, C_d^F breaks down overall connectivity into discrete pieces that add up to the original connectedness metric (Barunik and Krehlik, 2018).

$$C_d^F = 100.\left(\frac{\sum \widetilde{\Theta}_d}{\sum \widetilde{\Theta}_\infty} - \frac{Tr\{\widetilde{\Theta}_d\}}{\sum \widetilde{\Theta}_\infty}\right) = C_d^W.\left(\frac{\sum \widetilde{\Theta}_d}{\sum \widetilde{\Theta}_\infty}\right) \quad (14)$$

To validate the results of the BK-18 estimates, the dynamic conditional correlation GARCH (DCC-GARCH) model is employed to examine the transmission of shocks within the network. This is an extension of the Bollerstev (1990) constant conditional correlation (CCC) estimator. The process involves two steps. Firstly, the conditional heteroskedasticity is calculated. This is otherwise regarded as the Bollerstev (1990) CCC. Subsequently, the generalisation of the Bollerstev CCC captures the dynamics in the correlation. This is what inspired the name dynamic conditional correlation.

4. Results

Inspired by Bossman et al. (2022), we adopted a lag length of one and a rolling window size of 100, with a forecast length of 10. According to Bossman et al. (2022), the 100-day rolling window represents an aggregation of a quarter of a year, accounts for time differences, and eliminates the exogenous specifications of the start and end periods of a crisis. We simulated the window size with 50 days for a robust assessment and confirmed consistent outcomes.

4.1. Dynamic Total Connectedness

doi:10.20944/preprints202603.2264.v1

The dynamic total connectedness index shows the overall connectedness between/among the variables in the system. It is the transmission of shocks from one variable to another. It provides a basis to assess the connectedness over different phases of economic or financial cycles.

4.1.1. Full Order Flow and Exchange Rate Data

The first plot under consideration is the full data covering the period 2018-2023. The plot in Figure 4.1 presents the total connectedness among all order flows and exchange rate variables employed for this study (USD/GHS, EUR/GHS, and GBP/GHS). The analysis has been segmented into a time-frequency domain. Scale 1-4 (red) represents short-term, scale 4-8 (green) represents medium, scale 8 to infinity (blue) represents long-term, and black represents the total connectedness. We observe that connectedness is relatively strong in the short term compared to other frequencies, implying that connectedness is more transitory than permanent. Total connectedness ranges between 38% and 45% and averages 30%. This level of connectedness can be described as significant, as alluded to by Kamesh and Aswini (2024), who described a 30% total connectedness index of financial instruments as significant and consistent.

The peaks in 2022 and beyond confirm the exchange rate crisis that hit the Ghanaian FX market in that period. This also corroborates the assertion that macro-financial variables exhibit strong interdependence during periods of crisis or contagion (see Louati et al., 2022). The periods before 2022, although exhibiting some oscillations, were quite stable compared to the post-2022 period.

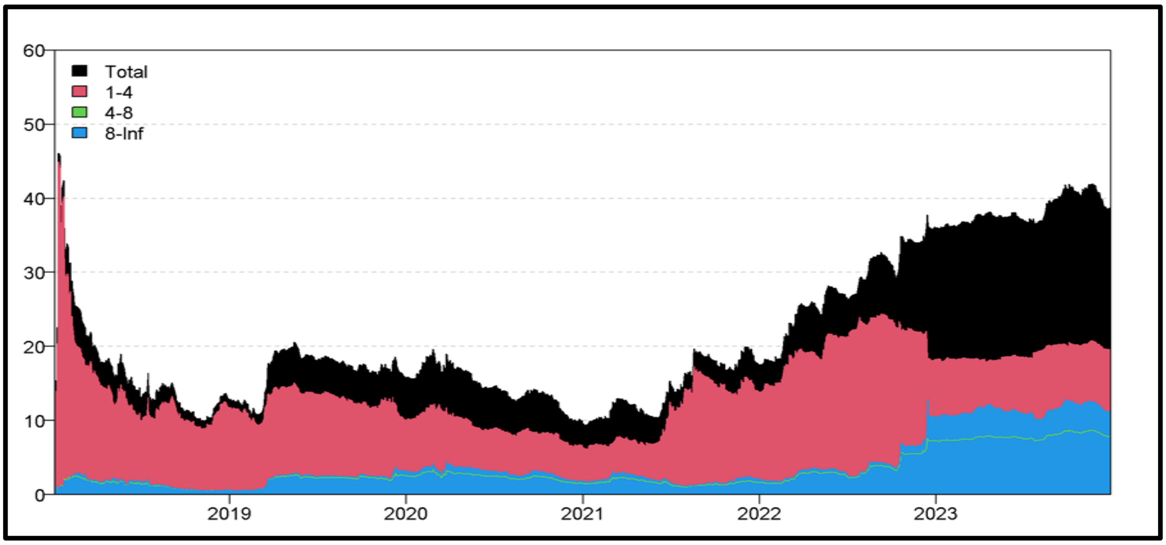
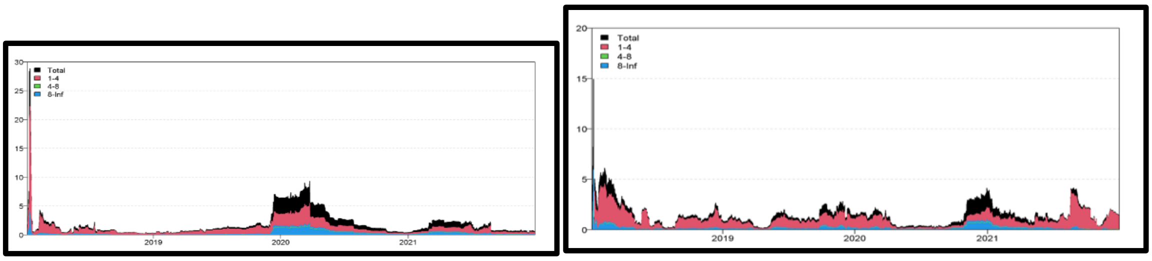


Figure 4.1. Full Sample Period Total Connectedness Index - All Order Flows and Exchange Rates.

4.1.2. Calm Market Conditions

Under this section, the data has been decomposed into calm conditions (2018-2021). Figures 4.2a, 4.2b, and 4.2c represent USD/GHS, EUR/GHS, and GBP/GHS, respectively. A cursory observation of the plots revealed that the total connectedness across all the currency pairs stood at around 5%.



a) **b)**

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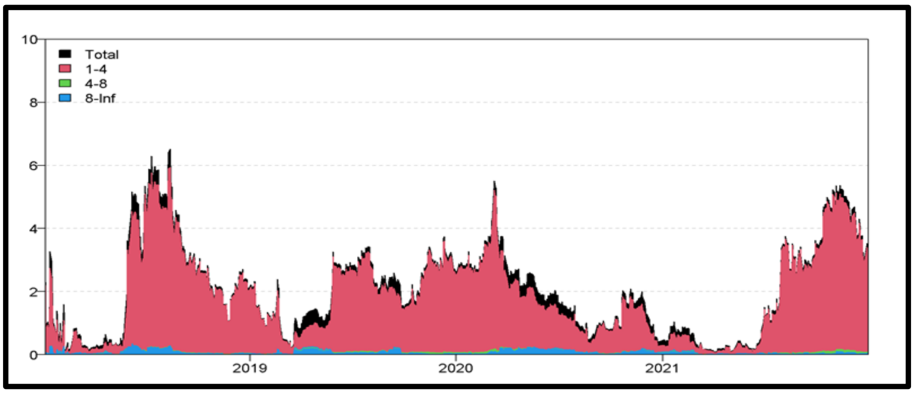


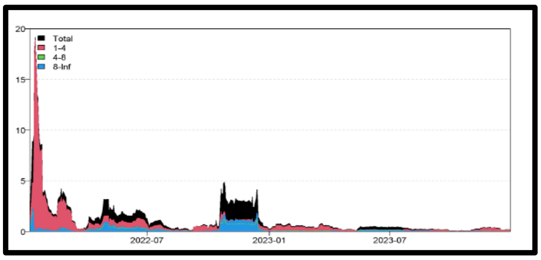
c)

Figure 4.2. Calm Market Conditions Total Connectedness Index – Order Flows and Exchange Rates.

Despite a weak connectedness between each pair in the calm market conditions, we observed that the GBP/GHS and, to some extent, the EUR/GHS were more volatile than the USD/GHS. Another major insight from the plots is that the connectedness is stronger in the short-term relative to the medium and long-term.

4.1.3. Turbulent Market Conditions

In Figures 4.3a, 4.3b, and 4.3c, we present the total connectedness during the turbulent market period (2022-2023). This represents the period when Ghana's FX market was hit by an exchange rate crisis. Firstly, the total connectivity across all the currency pairs ranged between 3% and 25%. A major spike was observed in 2022 when the crisis was rife. The short-term frequency continued to exhibit a stronger connectedness. Similarly, the EUR/GHS and GBP/GHS witnessed more spikes than the USD/GHS.



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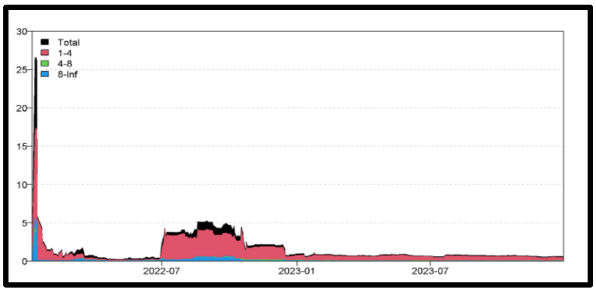

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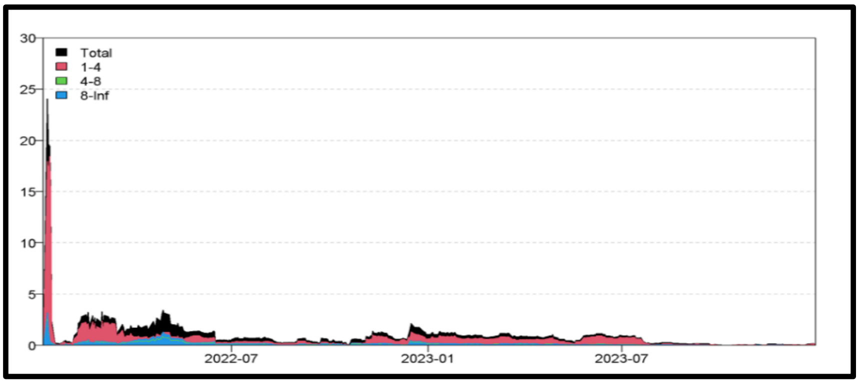

c)

Figure 4. 3: Turbulent Market Conditions Total Connectedness Index.

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4.2. Net Total Directional Connectedness

We investigate the net directional connectivity to ascertain whether a variable operates as a net transmitter or recipient of shocks. This refers to the difference between the shocks transmitted and received by a variable. Positive values indicate that a variable is a net transmitter of shocks, while negative values indicate that the said variable is a net recipient of shocks within the system.

Just like the total connectedness, the analysis is done over the full data period, including calm and turbulent market conditions. Additionally, the analysis is extended to the global sentiment and order flows. The time-frequency domain helps us to understand the dynamics in the short, medium, and long term.

4.2.1. Full Order Flow and Exchange Rate Data

The results of the full data covering 2018 to 2023 are presented in Figure 4.4 below. The colour codes and frequency analysis as posited in the total connectedness remain.

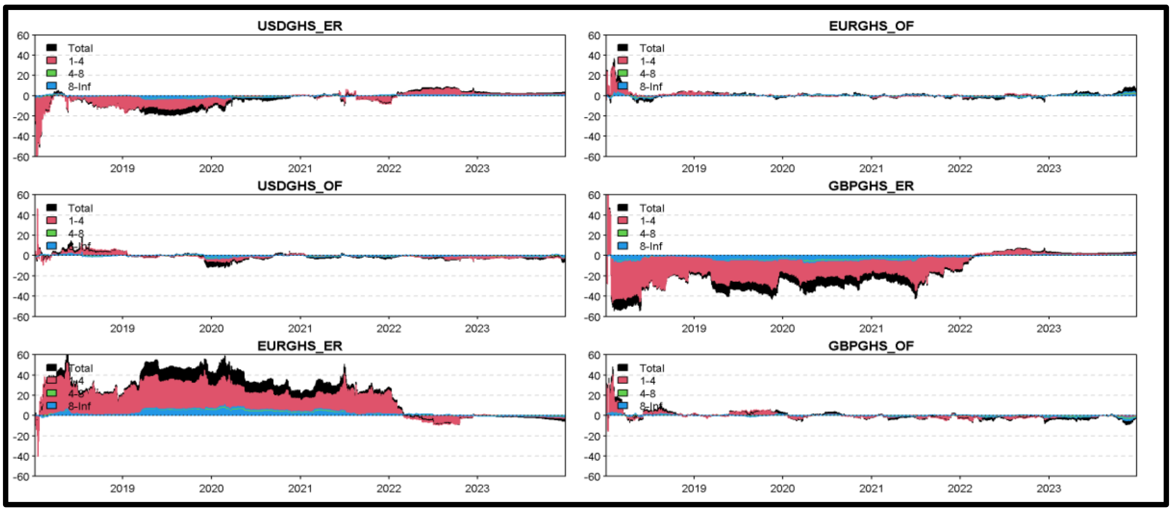


Figure 4. 4: Net Total Directional Connectivity - All Order Flows and Exchange Rates.

From Figure 4.4 above, we observed that the USD/GHS exchange rate played a dual role as a net transmitter and recipient of shocks. Specifically, it was a net recipient of shocks during the calm market conditions between 2018 and 2021. However, from 2022, it turned out to be a net transmitter of shocks to the system. The GBP/GHS exchange rate emerged as a dominant net recipient of shocks, while the EUR/GHS exchange rate stood out as a net transmitter of system shocks. For the order flow data, the transmission-receiving roles were weak and interchangeable across the sample period.

4.2.2. Calm Market Conditions

In the context of net total connectedness during the calm market conditions (Figure 4.5), it was observed that the USD/GHS, EUR/GHS, and GBP/GHS exchange rates and order flows exhibited dual roles of net transmissions and reception across the sample period. However, in the early stages of the period in 2018, the EUR/GHS order flow was a net transmitter to the EUR/GHS exchange rate, mainly in the short term. For the GBP/GHS, the order flow was a dominant net transmitter of shocks to the exchange rate.

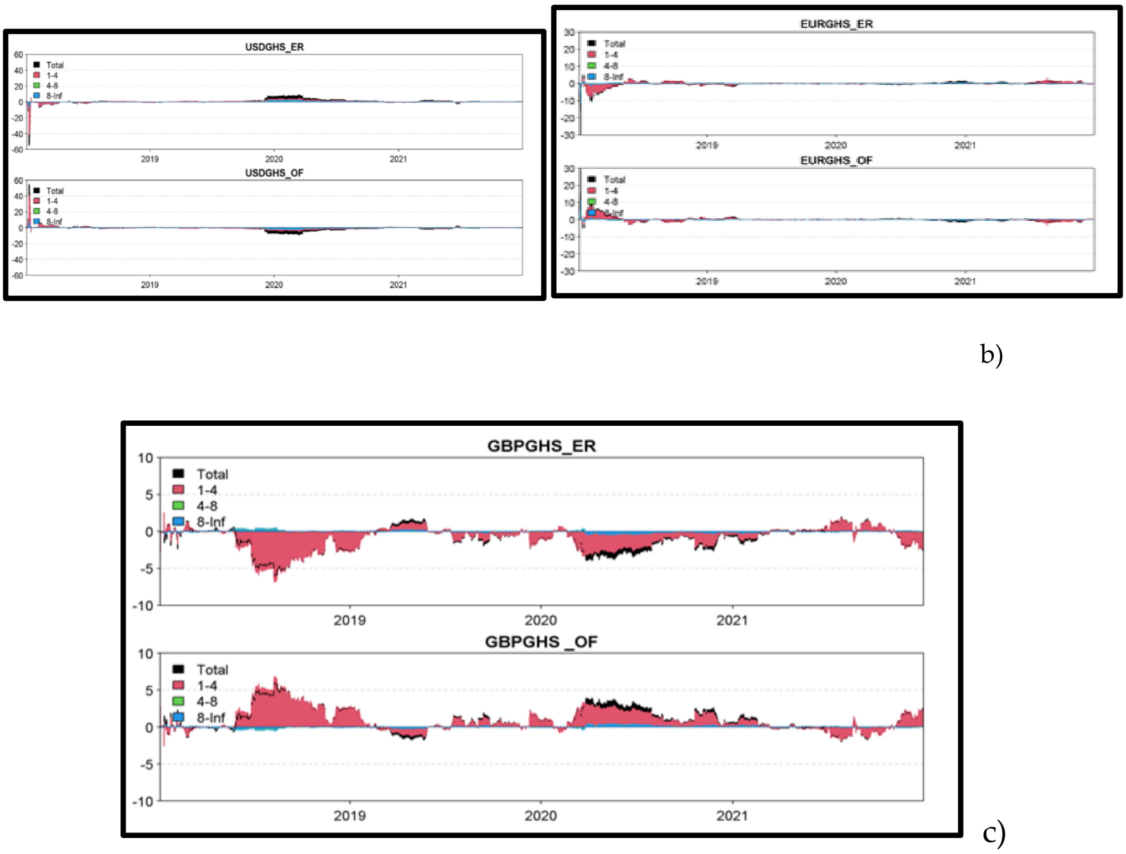
4.2.3. Turbulent Market Conditions

In Figure 4.5, there was a unanimous trend about order flows passing on shocks to exchange rates in the calm market conditions. However, that trend changes slightly during the turbulent market conditions (see Figure 4.6). For example, only the USD/GHS had order flow transmitting shocks to exchange rates, with a high magnitude of shocks observed in the early part of 2022.

doi:10.20944/preprints202603.2264.v1

Conversely, the exchange rate was the source of shock transmissions to order flows in the case of the EUR/GHS and GBP/GHS. This was observed through a dominant net transmission with the peak occurring in the early part of 2022 within the short-term frequency domain.

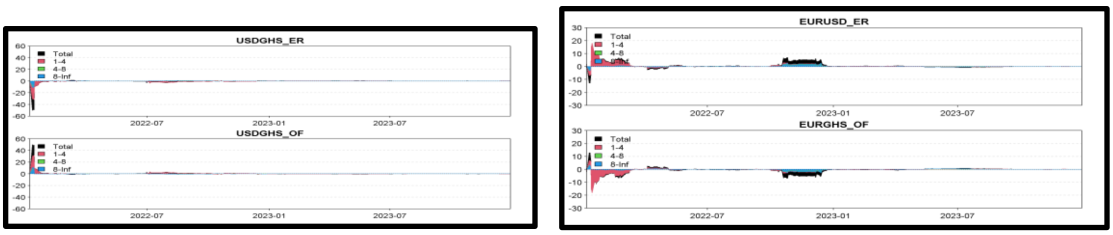
In the entirety of 2023, the shocks from exchange rates to order flows for the GBP/GHS were persistent, indicating that trading volumes responded directly to the movements of the exchange rates. This was also within the short-term frequency, underscoring the immediacy of shocks. The shocks from the EUR/GHS exchange rate to order flow were profound in the early stages of 2023.



a) b)

c)

[4]**Figure 4.5.** Calm Market Conditions Net Total Connectedness Index – Order Flows and Exchange Rate- a) USD/GHS b) EUR/GHS c) GBP/GHS.



a) b)

[4] NB: The average connectedness is almost the same. Figures 4.6a and 4.6b had extended scales to accommodate one-off peaks in the early part of the respective periods.

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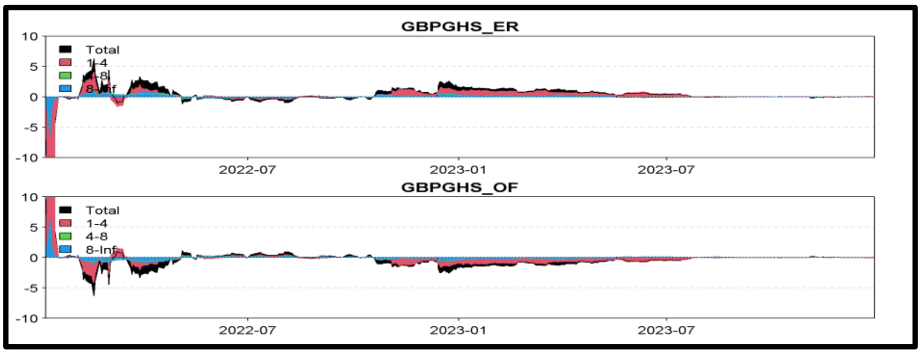
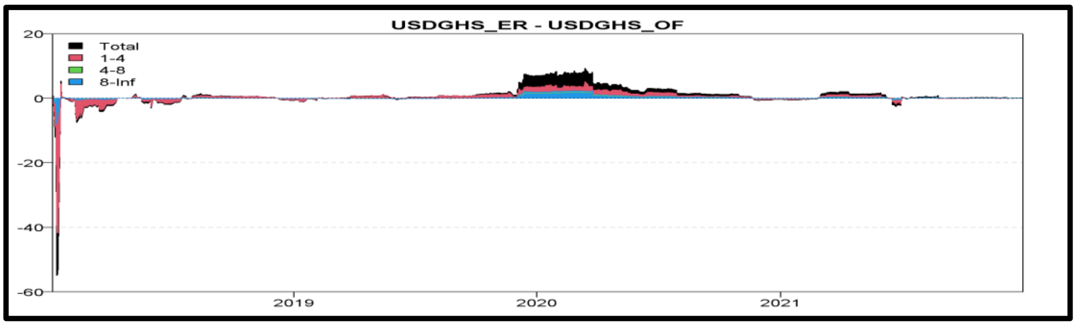


c)

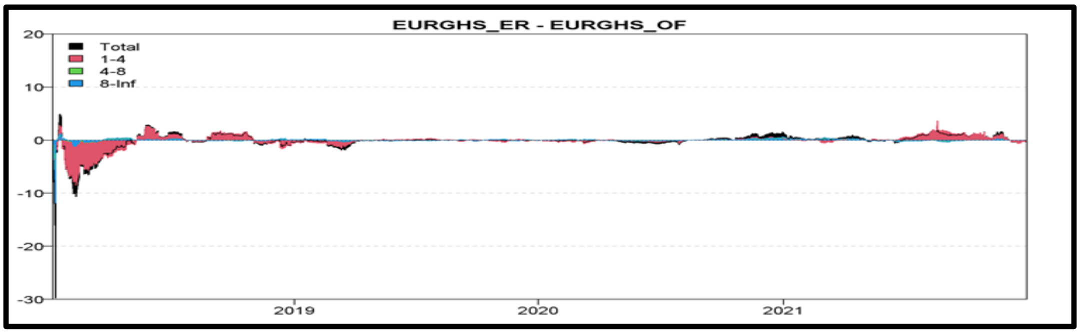
Figure 4.6. Turbulent Market Conditions Net Total Connectedness Index – Order Flows and Exchange Rate- a) USD/GHS b) EUR/GHS c) GBP/GHS.

4.3. Net Pairwise Directional Connectedness

In this section, we assess the pairwise connectedness between each pair of order flows and exchange rates regarding the currency pairs. This provides a basis to ascertain the net transmission or receiving status of the pair. For example, we can tell how the combined effect of the USD/GHS order flow and exchange rate varies from the EUR/GHS and GBP/GHS pairs. This analysis is also done over calm and turbulent market conditions, as seen in Figures 4.7 and 4.8.



a)



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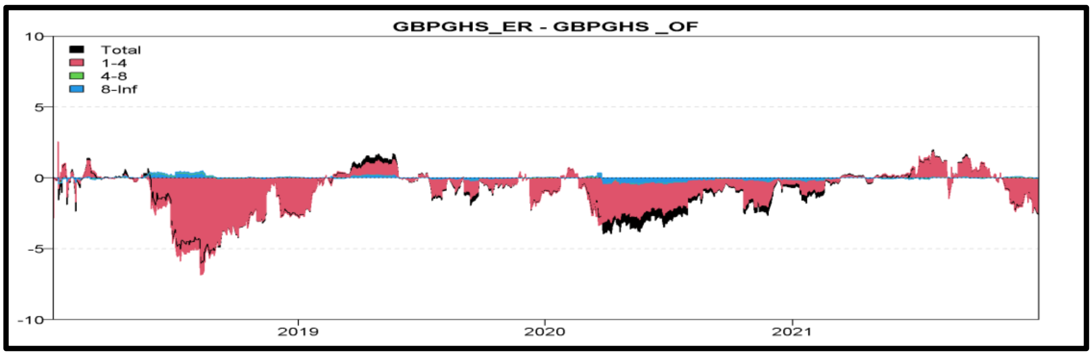

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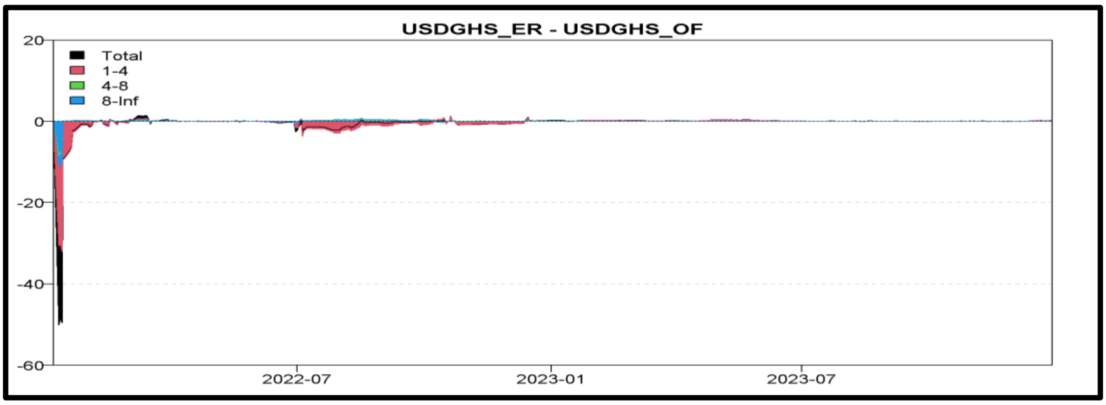
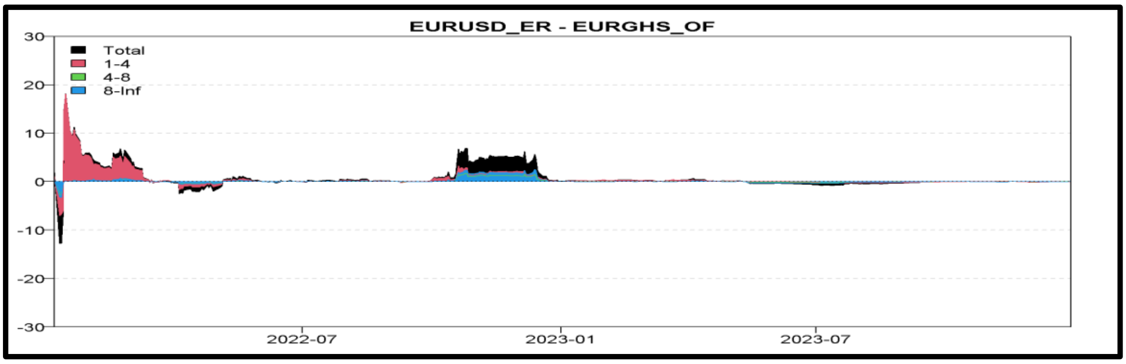
c)

Figure 4.7. Calm Market Conditions Net Pairwise Connectedness Index – Order Flows and Exchange Rate- a) USD/GHS b) EUR/GHS c) GBP/GHS.

From Figure 4.7, it is observed that the USD/GHS and the EUR/GHS pairs showed no distinct dominant transfer direction. In other words, they interchanged the net transmission and reception roles. However, the GBP/GHS pair showed a dominant net transmission trend across the sample period.



a)



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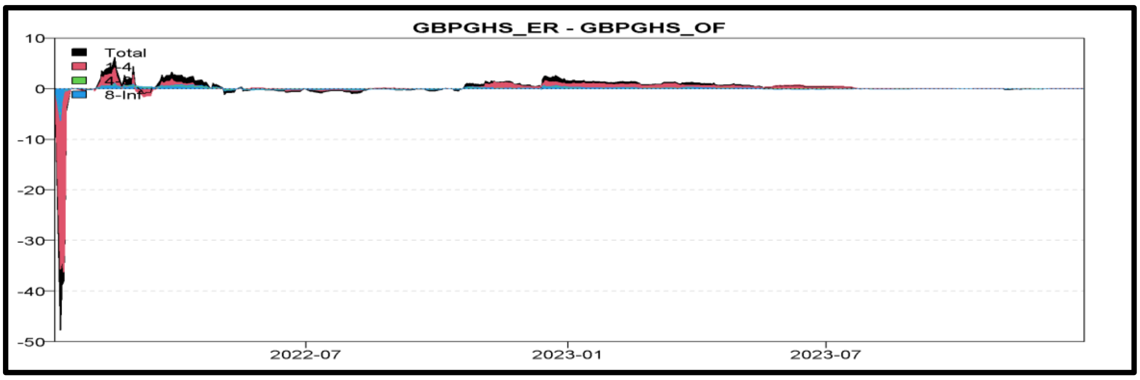

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Figure 4.8. Turbulent Market Conditions Net Pairwise Connectedness Index – Order Flows and Exchange Rate- a) USD/GHS b) EUR/GHS c) GBP/GHS.

Figure 4.8 shows that during turbulent market conditions, the USD/GHS order flow and exchange rate pair were the dominant net recipients of shocks, while the GBP/GHS and EUR/GHS order flow and exchange rate pairs were the dominant net transmitters. This suggests that the volatility of the USD/GHS pair could also be driven by spillovers from the EUR/GHS and GBP/GHS pairs.

4.4. Net Dynamic Network Connectedness

The BK-18 plot visually represents the interconnectedness and spillovers among variables within a system. The plot traces how shocks are exchanged among variables while identifying the net transmitters and recipients of shocks. The analysis is done within a time-frequency domain in the short, medium, and long term. As done in the previous analysis, dynamic connectedness is compared between calm and turbulent market conditions. From the plots, the blue nodes represent the net transmitter role, while the yellow nodes indicate the receiver of shocks. The node sizes are a representation of the magnitude of the shocks. Meanwhile, the vertices measure the weighted average net pairwise directional connectivity.

In Figure 4.9, we first present the full data network connectedness plots. In line with the time-frequency domain, the plots are displayed in short, medium, and long-term from left to right. On the extreme right is the total network connectedness without any decompositions. From the short to long term, we observed that the EUR/GHS exchange rate was a transmitter of shocks to the USD/GHS and GBP/GHS exchange rates. However, the USD/GHS, EUR/GHS, and GBP/GHS order flows, although showing potential transmission and receiving roles, failed to connect the shocks to the system. It was mainly observed that the EUR/GHS order flow was consistently a potential net transmitter of shocks.

For the total dynamic connectedness, the EUR/GHS exchange rate continued to transmit shocks to the USD/GHS and GBP/GHS exchange rates. Meanwhile, the EUR/GHS was a potential transmitter of shocks, while the USD/GHS and GBP/GHS order flows were potential net recipients. The results from the full data plots indicate that the EUR/GHS exchange rate is a source of shock spillover to the USD/GHS and GBP/GHS exchange rates, while the EUR/GHS order flow has the potential to emit shocks.

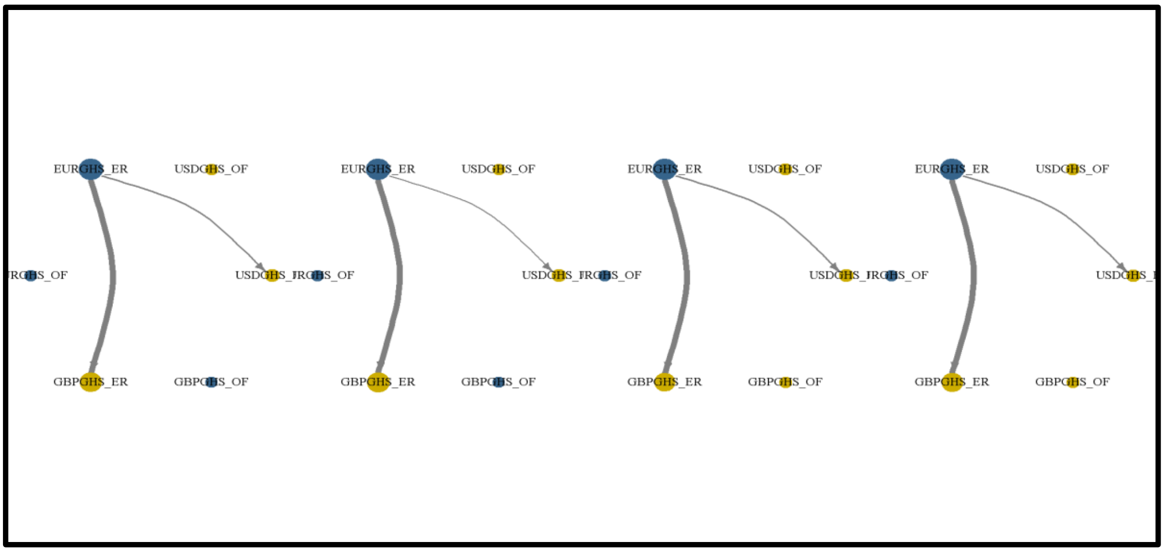


Figure 4.9. Full Data Dynamic Network Connectedness Plot – Full Data Sample.

Having analysed the full sample period, we move on to the calm and turbulent market conditions for the three currency pairs. For USD/GHS, the dynamic network connectedness plots for the calm and turbulent market conditions are presented in Figure 4.10 and Figure 4.11, respectively. It was observed that during the calm market conditions, the USD/GHS exchange rate transmitted shocks to order flows in the short, medium, and long term. The same trend was also observed in the total connectedness plot. On the back of this, it is unanimously ascertained that the movements of the USD/GHS drive trading patterns when market conditions are stable. On the contrary, regarding the turbulent market conditions, the relationship was not unidirectional. For example, in the short and medium term, exchange rates are impacted by shocks from order flow, while the trend reverses in the long term and the total plot. Given the importance of short-term exchange rate volatility, the most profound insight is the transmission of shocks from order flows to exchange rates from the short to medium term.

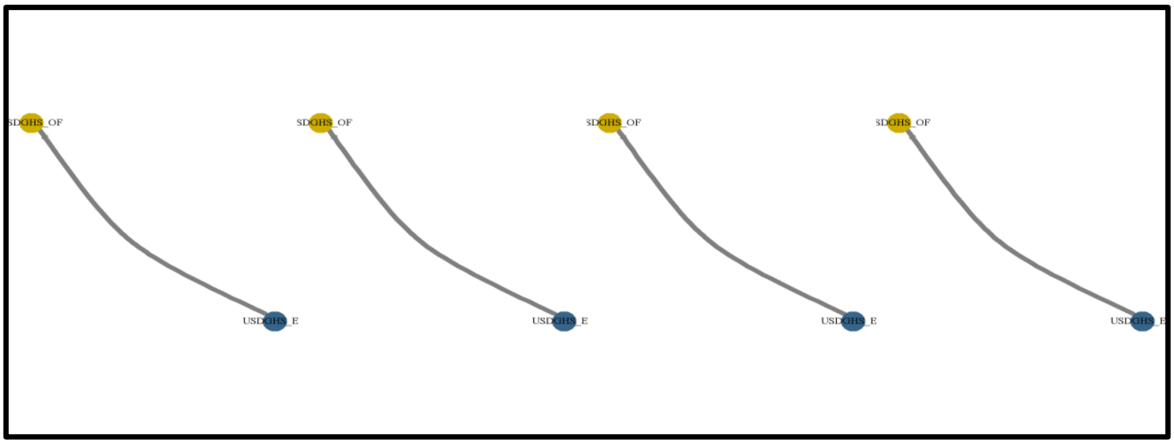


Figure 4.10. Calm Market Conditions USD/GHS Dynamic Network Connectedness Plot.

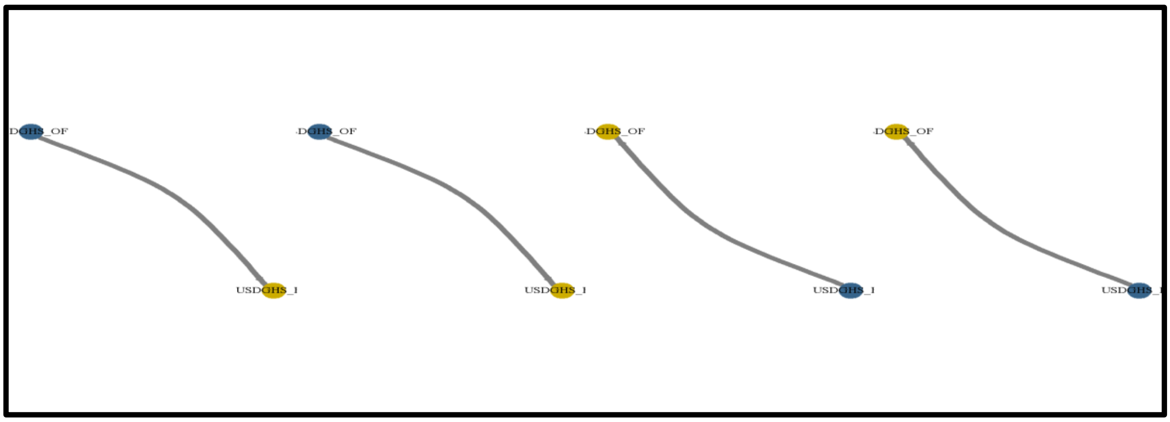


Figure 4.11. Turbulent Market Conditions USD/GHS Dynamic Network Connectedness Plot.

Meanwhile, during calm market conditions, the EUR/GHS order flows transmitted shocks to exchange rates across all frequencies and the total plot (Figure 4.12). However, during turbulent market conditions, the relationship switched as order flows exchange rates transmitted shocks to order flows (Figure 4.13). Interestingly, the GBP/GHS also posted the same trend in both calm and turbulent market conditions across all frequencies (see Figures 4.14 and 4.15). This indicates that trading volumes are influenced by the direction of the exchange rates in extreme market conditions, with the EUR/GHS and GBP/GHS.

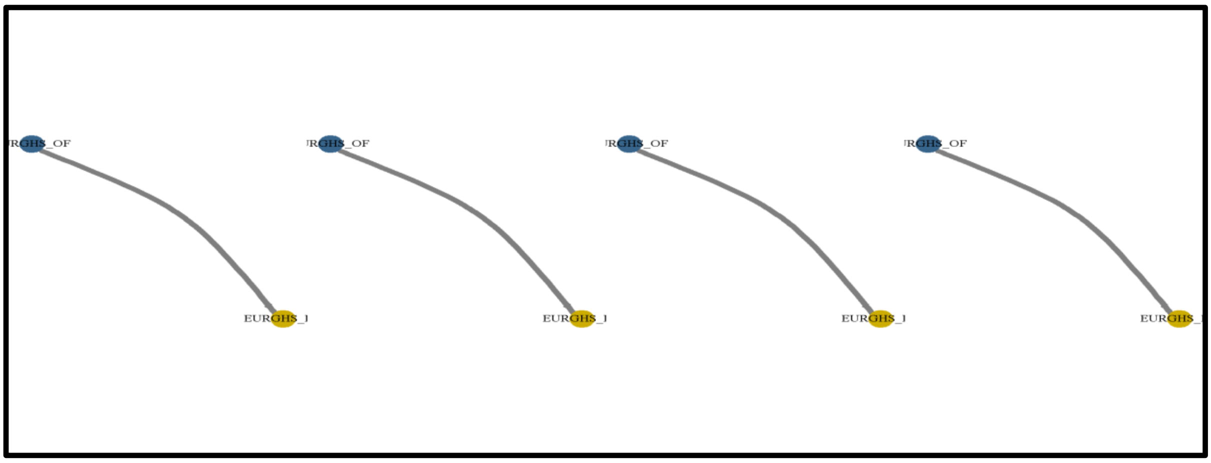


Figure 4.12. Calm Market Conditions EUR/GHS Dynamic Network Connectedness Plot.

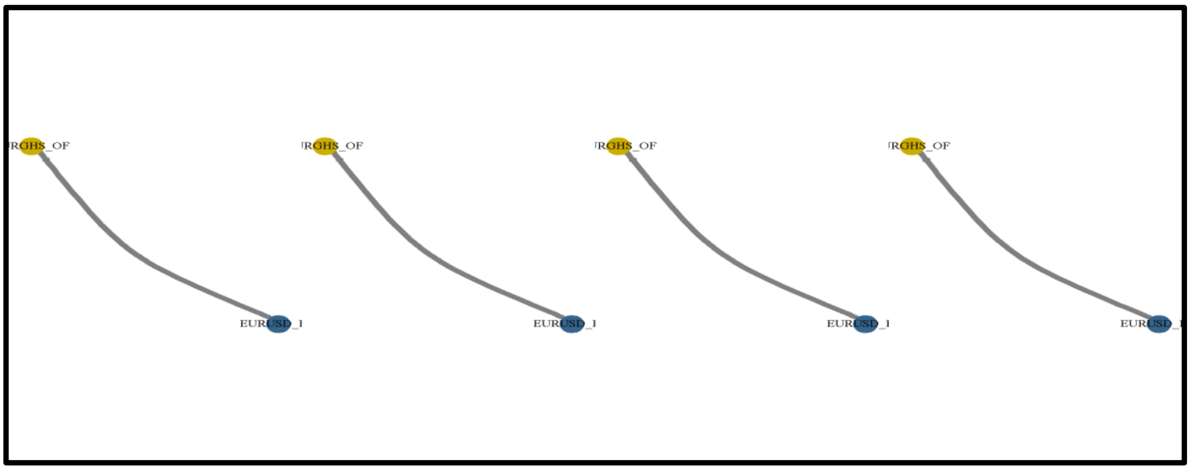


Figure 4.13. Turbulent Market Conditions EUR/GHS Dynamic Network Connectedness Plot.

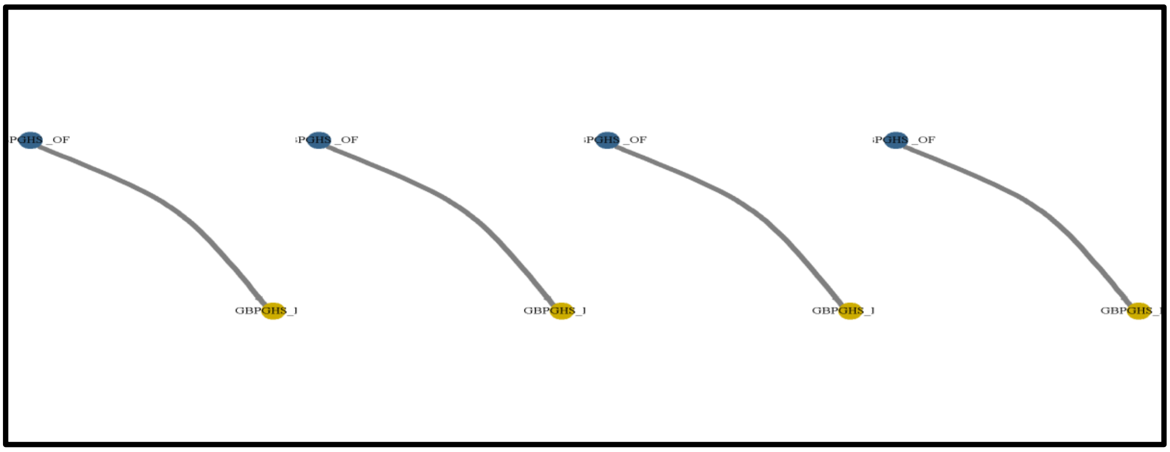


Figure 4.14. Calm Market Conditions GBP/GHS Dynamic Network Connectedness Plot.

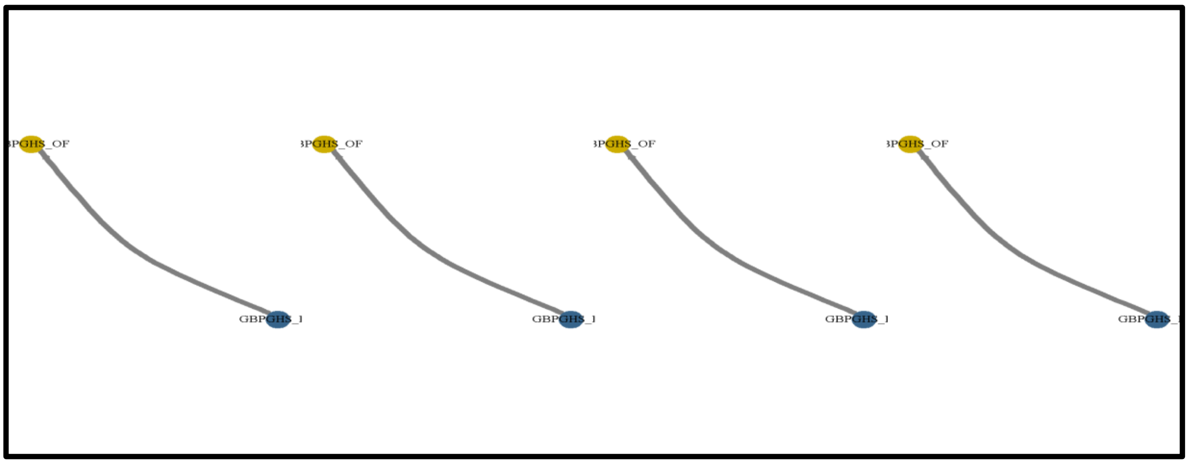


Figure 4.15. Turbulent Market Conditions GBP/GHS Dynamic Network Connectedness Plot.

4.5. Discussions

From the results, it was observed that there is a relatively strong connectedness in a multivariate system of order flows and exchange rates for the three major currencies in Ghana — USD/GHS, EUR/GHS, and GBP/GHS. This implies that despite the USDGHS being the dominant trading currency in Ghana, shocks could be transmitted from the EUR/GHS and GBP/GHS, which are considered minority currencies. For example, within the multivariate framework of shocks exchanges, it was found that the EUR/GHS exchange rate is a major transmitter of shocks, with the major recipients being the USD/GHS and GBP/GHS exchange rates.

This implies that the pricing of the EUR/GHS could account for the movements of the USD/GHS currency pair, especially in times of depreciation. This confirms a nuanced observation in the Ghanaian FX market, where cross-currency trades become pronounced in times of U.S. liquidity tightness. In this instance, the GHS is used to acquire the EUR in the Ghanaian market. The EUR subsequently becomes the conveyor belt to source U.S dollars from counterparties in other markets to fill liquidity needs in the Ghanaian FX market at higher rates. These higher rates stem from the premium pricing on such round-cycle transactions. The EUR may be a preferred vehicle currency for such cross-currency trades because the EUR/USD is the most liquid currency pair globally. Additionally, the EUR/USD is more stable compared to the GBP/USD. It was observed that this trend was muted in 2024. It could be inferred that the trend reversed after the FX crisis period 2022-2023.

When the analysis is decomposed into calm and turbulent market conditions, the results show that order flows and exchange rates are more correlated or share a higher interdependence in times of turbulence. The observation is in line with a general assertion that markets, or financial assets, are more correlated in times of crisis or contagion (Troug and Murray, 2020). Most importantly, our results also revealed a bidirectional relationship between order flows and exchange rates, as established in the existing literature (see Koosakul and Ananchotikul, 2018). For the USD/GHS, it was revealed that exchange rate transmitted shocks to order flows in calm market conditions. However, in turbulent conditions, order flows predominantly (in the short and medium term) and transmits shocks to exchange rates. This aligns with the earlier remarks about cross-trading in search of dollar liquidity, in periods of extreme currency depreciation, which are often characterised by liquidity crises. For the EUR/USD and GBP/USD, there was unanimity in the trends. Order flows transmitted shocks to exchange rates in calm conditions, while exchange rates transmitted shocks to order flows in turbulent conditions. The relationship was consistent within the time frequency domain across the short, medium, and long-term.

A simple observation gleaned from these results points to the fact that in extreme market conditions, traders are prepared to fill their dollar needs regardless of the price. In essence, if liquidity is made available, there is a strong urge to close the transactions. We can draw linkages with the findings of Anifowose et al. (2018), whose results indicated that order flows explain an important portion of the movement of the Malaysian currency against the USD. However, for the minority currency pairs such as the EUR/GHS and GBP/GHS, traders are more concerned about pricing in turbulent periods.

The interdependence between order flows and exchange rates grows stronger at the bullish end of the market, implying that when prices (rates) are rising, there is a strong bidirectional connectedness between exchange rates and trading volumes. This may not be surprising on the back of general observations that markets, or financial assets, are more correlated in periods of excess volatility or contagion (Kleinbord and Li 2017). On the other hand, at the bearish end of the market, the correlation between order flows and exchange is negative, implying that when prices (rates) are falling, trading volumes and exchange rates move in opposite directions. This is practically true because when the GHS appreciates (USD/GHS falling), there is a significant increase in FX liquidity as market players offload forex to reduce their losses. At the same time, others (especially importers) also take advantage of the trend to enter long positions to facilitate trade at cheaper costs.

5. Conclusions and Recommendations

This study contributes to the existing literature on exchange rate economics within the microstructure framework in Ghana. We examine the connectedness between order flow and exchange rate from a multivariate approach, concerning three major trading currency pairs—USD/GHS, EUR/GHS, and GBP/GHS. We aimed to extract insights during calm and turbulent market conditions. We also attempted to trace the source of shocks in the multivariate system and how order flows respond to global uncertainties. Based on the results, the following findings were extracted.

- A bidirectional causality between order flows and exchange rates
- The EUR/GHS is a major transmitter of shocks to a multivariate system of order flows and exchange rates
- Relatively strong connectedness among order flows and exchange rates covering the USD/GHS, EUR/GHS, and GBP/GHS, with the EUR/GHS being the major transmitter of shocks to the system
- In calm market conditions, the USD/GHS exchange rate drives order flows; meanwhile, in turbulent market conditions, order flow accounts for the exchange rate movements in the short and medium term. For the EUR/GHS and GBP/GHS, order flows account for exchange rate movements in calm conditions, while the opposite holds in turbulent market conditions.
- A strong interdependence between order flow and exchange rate at the bullish end of the market.

We can infer that optimal foreign exchange (FX) liquidity is a contributing factor to market stability in Ghana. The reactions and responses by traders across the time-frequency domain, currency pairs, and calm/turbulent market conditions align with the properties of the heterogeneous and adaptive market hypotheses. Our results possess significant information content for FX regulation and monitoring, FX interventions, and FX trading.

Since the FX market reflects information in real-time, it will be crucial to build high-frequency data (e.g., hourly or intraday) to model this nexus with granular details in subsequent research. Additionally, the Ghana cedi has witnessed a tremendous departure from previous times by posting a significant cumulative appreciation of 40.67%, 30.89%, and 23.97% against the USD, EUR, and GBP, respectively, by the end of December 2025 (data sourced from the Bank of Ghana). It will be insightful to test this relationship in a period of record-sharp currency appreciations. Finally, a local metric for economic uncertainty/sentiment can be decomposed into daily frequency to empirically ascertain whether order flows respond faster to domestic or global factors.

The results/findings of this study have implications for FX monitoring and regulation in Ghana. Firstly, the identification of the EUR/GHS exchange rate as a source of shock transfer to a multivariate framework of USD/GHS, EUR/GHS, and GBP/GHS order flows and exchange rates is an important discovery. Having observed that this phenomenon could be triggered by USD liquidity shortage

doi:10.20944/preprints202603.2264.v1

through cross-currency trading, it will be expedient to factor this into the Bank's market intervention or support strategies. In periods of USD liquidity shortage, market interventions or support should be timely and optimal to prevent a pick-up in cross-currency trades with the EUR as the conveyor belt to fill USD liquidity needs. It also calls for a closer observation of cross-currency trades (particularly the EUR/USD) to appreciate the trends and sources. Therefore, although the EUR/GHS remains a minority trading currency relative to the USD/GHS, its status as a potential emitter of shocks makes it imperative to give such minority currency pairs a greater prominence in the Bank's FX monitoring architecture. It is important to note that this development disappeared in 2024 as the EURGHS transitioned into a marginal net recipient of shocks. We can, therefore, infer that this is profound in times of market crisis or periods of tight FX liquidity.

Having found that exchange rate and order flow share a stronger interdependency in bullish forex conditions, this further corroborates the fact that market interventions are a key consideration for adequate FX reserve build-up. Being an emerging/frontier economy central bank, it is important to build adequate FX reserves to help smooth the volatility of the currency in periods of crisis or rising exchange rates through FX interventions. This will put the Bank in an optimal position to support the market. Our findings revealed that in calm market conditions, when there is stability, order flows are driven by exchange rates, but the reversal holds in turbulent market conditions, implying that FX liquidity is key to the exchange rate market. Therefore, this study has implications for FX monitoring/regulation, FX intervention strategies, and FX reserves build-up.

Author Contributions: CRediT: Umar-Farouk Atipaga: Conceptualisation, Data curation, Formal analysis, Methodology, Writing – original draft, Writing – review & editing.

Funding: The authors received no direct funding for this research.

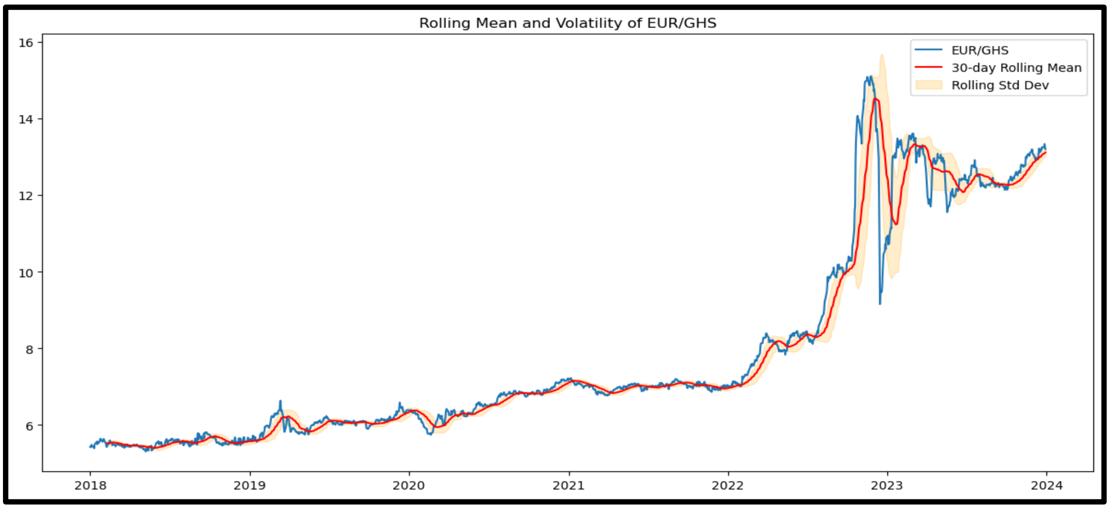
Statement of Competing Interest:_The Author declares no known competing financial interest or any relationships that could influence the outcome of this paper.

Public Interest Statement: This research offers significant value to all participants in Ghana's foreign exchange (FX) market, including policymakers, regulators, and FX traders. By uncovering the underlying microstructure of the Ghanaian FX market, it deepens understanding of market behavior and dynamics. The findings have practical implications for trading strategies, market monitoring, and the development of effective regulatory and policy frameworks.

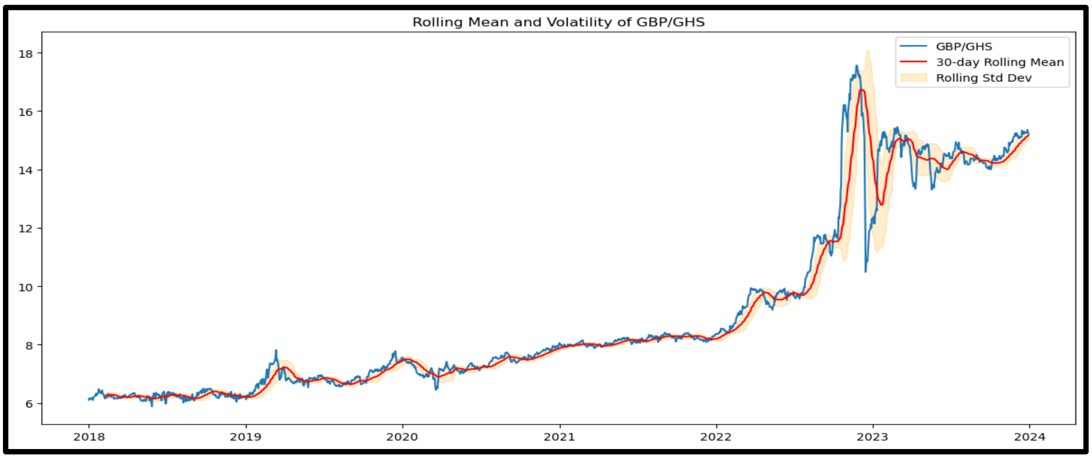
Acknowledgments: I acknowledge Professor Ian Marsh of Bayes Business School, City St George's, University of London, whose valuable suggestions and comments have contributed significantly to the quality of this work. I approve this final version for publication and affirm that I am fully accountable for all aspects of this research.

Disclosure statement: No potential conflict of interest was reported by the author.

Appendix



Appendix 1. 30-Day Rolling Mean and Volatility of the Nominal EUR/GHS Exchange Rate.



Appendix 2. 30-Day Rolling Mean and Volatility of the Nominal GBP/GHS Exchange Rate.

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