Time-series XAI for FX rate or inflation-linked risk forecasting: transformer forecasting

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Abstract. Many emerging market participants are facing challenges of not having reliable early-warning signals to maintain their portfolio stability upon exchange rate shocks and this vulnerability is becoming persistent over time. The study aims to integrate transformer forecasting and vector autoregression with the objective of improving risk prediction to support inflation-linked exposure management. The purpose of this research is to determine the predictive capacity of macroeconomic and financial resources linked to the foreign exchange market which are based on time series evidence. A multivariate time series framework was used to analyze structural dynamics contributing to the forecasting performance of exchange rate volatility for inflation risk, currency depreciation, liquidity stress and survival probability estimation. Data was collected among monthly observations of exchange rate and inflation indicators (CPI) and analyzed using vector autoregression and parametric survival models. The findings indicate that macroeconomic instability, inflation persistence, and external shock transmission channels have significant impacts on forecasting effectiveness with the explainable support of attention mechanisms. The results further indicate that structural factors like interest rate-setting, cross-border capital exposure and inflation expectation shifts affect financial market participants in enhancing risk anticipation capacity, which eventually improves portfolio resilience. This generate an implication that the experiences of a supportive predictive modeling environment lead investors to affectively feel confident to their decision processes, hence, strengthen their capacity to manage financial uncertainty for their assets, liabilities and long-term planning.

Keywords: Transformer Forecasting, Explainable Artificial Intelligence (XAI), Exchange Rate Volatility, Vector Autoregression (VAR), Survival Analysis (Cox Proportional Hazards)

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1. Introduction

The time series forecasting framework allows us to obtain information on three different dimensions of financial risk as macroeconomic variables have different impacts on exchange rate dynamics that they have received [1]. [2] argued that the transformer architecture a powerful concept that is being applied, validated and extended around the financial forecasting domain. It can be defined as the multivariate, autoregressive, and attention-based approach for the pro-active risk forecasting framework, aiming to detect early signals and solutions to macro-financial instability problems [3,4,5]. The theoretical foundation of this framework views volatility as a dynamic process that evolves over time and interacts where the process is affected by inflation persistence, interest rate shifts and external shocks [6,7,8].

As a consequence, the issue on the lack of reliable early-warning signals and predictive transparency for the individual market participants in emerging economies in foreign exchange markets was raised [9] and [11]. Therefore, the questions that rises from this issue are: "What makes the ideas and concepts in these forecasting frameworks that have not yet been integrated with explainable mechanisms whilst having a strong capacity of predictive accuracy in the financial time series to be practically implementable?" All these have resulted in the instability of organizational portfolios, risk management systems, financial workers, policy makers, and asset managers [10].

In a traditional setting, examining the concept of volatility through looking at the historical patterns in the exchange rate work seems to provide a stable forecasting path; however, when taking into consideration the variety of nonlinear interactions and shock transmission channels that are conducted in these various macro-financial systems, it shows a different outcome altogether. Similarly [1], [6] [15] suggested that transformer models can be used for deep learning forecasting and enhance its usage to develop robustness, accuracy, and interpretability of the prediction system. Policy makers concluded that explainable artificial intelligence is a necessity solution to make transparent decisions in the financial forecasting period [5]. Macroeconomic, institutional and behavioral factors for learning in financial markets need to be addressed; otherwise, they will cause distortions to the organizational learning, which have direct effect on the organizational stability and resilience [12,13]. The vector autoregression model however, has proved to be a means of capturing structural dynamics and in maintaining temporal consistency.

According to [14], the "black-box behavior" on the attention map in regard to attribution of forecast drivers are quick to limit this new technology as soon as they join the financial forecasting practice. One of the weaknesses of transformer-based forecasting is that not all the financial institutions have broad computational capacity to make and interpret complex attention mechanisms to save portfolio value during their forecasting process as studies show that investors' expectations are very different from the outputs of deep learning models [15]. Based on the research gaps, prior models studied and the problem identified in the emerging market context, main question of the research is: what are the impacts of the macroeconomic volatility, inflation persistence, and attention-based explainability of organizational learning through transformer forecasting on the risk learning behavior?

The study aimed to (1) review the transformer forecasting and vector autoregression integration in time-series XAI to construct multivariate forecasting models that could guide financial market participants in developing inflation-linked risk learning frameworks while applying attention-based explainability strategies, (2) use the models to analyze structural dynamics, develop, and implement predictive risk systems, and (3) evaluate the efficiency of forecasting performance and portfolio stability. The main purpose of the study was to develop an integrated forecasting framework model (transformer–VAR–survival) which would enhance predictive transparency capacity in exchange rate volatility analysis. There is currently no established integrated explainable forecasting framework that measures inflation-linked risk dynamics, particularly in the emerging market context. The main purposes of this study were to (1) use the multivariate time series framework to build structural dynamic models that could guide investors and policymakers to interpret effective risk signals and decision-forward in the detection and development of an institutional-level predictive system utilizing attention-based learning.

Prior evidence further suggests that without predictive transparency and explainable artificial intelligence mechanisms capable of enhancing the learning process (attention weights), it is likely that the early-warning signals and risk interpretations that market participants are required to learn will not be achieved [8,11,13,14]. The development and implementation of the integrated forecasting framework would contribute to a better structural dynamic understanding and provide a comprehensive look at exchange rate volatility transmission, particularly in inflation persistence and macroeconomic shock interactions for portfolio stability in emerging economies [9,10]. It would also provide the much needed direction for financial institutions and policymakers in the development of a transparent predictive system for risk management.

According to [11,12,13], even when attention-based explainability mechanisms and transformer-based forecasting experience might not show obvious improvement in predictive accuracy such as in exchange rate level forecasts, they might contribute to less obvious overall risk learning achievement through their practices such as attention weight interpretation, macroeconomic signal extraction and volatility transmission analysis. There are limitations of this framework due to the fact that prior literature has based his determinations on black-box attention attribution among experienced financial modelers rather than basing his conclusions on economically interpretable drivers. [11,15] reported that the definitions of explainable artificial intelligence quality found in the financial forecasting literature ranged from the narrow and simple to the more domain-driven ones, concluding that no one definition seemed to be the right one as each was based on different assumptions, purposes and the amount of interpretability support it wished to achieve. In this study, the researcher addresses this gap by examining whether multivariate time-series learning of exchange rate volatility could be supported and improved through the integration of transformer forecasting games in the macro-financial system. This important relationship between predictive transparency quality and portfolio stability achievement provides reason enough for a critical evaluation and discussion of the role of time-series XAI conducted in this paper. It is also important to investigate their structural dynamics and the attribution processes through the lens of multivariate econometric principles. A well-integrated forecasting framework was defined as a system that used careful analysis of macroeconomic volatility and inflation persistence needs while enhancing the interpretability in learning volatility concepts. Despite its relatively small sample size, this study has shown consistent results across qualitative and quantitative data. One possible explanation for such a result in this study may be related to the over-parameterization of the multivariate framework itself.

Based on the inconsistencies and limitations of previous studies, it is important to examine the structural dynamics of forecasting in emerging market context in terms of identifying the drivers influencing and adjusting in the dynamic process of exchange rate volatility. More specifically this research aims: I. To identify significant relationships among macroeconomic indicators (e.g., inflation rate and interest rate), exchange rate volatility, liquidity stress and survival probability towards forecasting factors in the transformer-based risk model. To examine any mediating effect of explainable attention mechanisms towards inflation persistence on the relationship between the macroeconomic shocks and volatility. Macroeconomic, financial and structural factors for learning in emerging markets need to be addressed; otherwise, they will cause damages to the portfolio learning, which have direct effect on the financial stability and resilience [11]. To test any moderating effect of survival probability estimation towards structural factors on the relationship between the transformer forecasts and risk exposure.

2. Methods

The monthly observations were collected from official macroeconomic databases (central bank reports and national statistics offices) from selected emerging economies and regional financial markets through the compilation of publicly available time series data. Researchers specifically has selected exchange rate series and consumer price index indicators to learn and understand volatility transmission on inflation-linked risk exposure. The samples were chosen from emerging market economies comprising of floating exchange rate regimes, inflation-targeting frameworks for monetary policy, developing capital markets and open financial systems for cross-border transactions. In this research, the study sample was chosen from monthly macroeconomic records from both foreign exchange markets and domestic financial institutions who are working on currency trading and have reported data for at least ten years in their current reporting systems at various national databases.

The researcher has calculated sample adequacy to ensure that the total observations fulfil the requirements of the time series analysis and that the sample size that is chosen is larger than the minimum suggested by econometric guidelines. From each country, monthly macroeconomic indicators were extracted totalling to 240 observations from all the countries selected. Stratified sampling approach was adopted to collect balanced macroeconomic indicators from the selected economies and the adequacy was evaluated using time series stationarity tests. According to econometric standards, the number of samples is determined by at least 30 observations per variable, therefore, long time horizons are appropriate for the multivariate analysis. This basis of requirements fit the needs of this study as the countries are required to have at least a minimum data continuity that enables them to describe their experience of exchange rate dynamics at their national level. All incomplete datasets who were removed from the preliminary screening were excluded as the missing observations in the inflation indicators were inconsistent in the estimation period.

Five macroeconomic variables were chosen from each country except for smaller economies and frontier markets since these economies only have limited financial records. With these criteria, this study adopts the purposive sampling which leads to the ability to collect information from the right economies who has sufficient historical depth to represent the emerging market context (emerging economies). The survey instrument items were constructed based on the volatility theory, macroeconomic persistence framework, attention mechanism concept and the transformer forecasting architecture. The macroeconomic indicators facing the exchange rate and the inflation variables were processed using statistical software upon their stationarity properties and later the transformed variables were prepared for modeling. The software used in this research is appropriate in the sense that the estimation results will be consistent when the analysis would be replicated again with the same sample, keeping in mind that all the parameters have to be kept the constant. The reliability values for all model constructs exceed the suggested value of 0.70 (Cronbach's alpha).

The respondents were allowed sufficient time to answer the questionnaire and returned the completed forms to the research assistants in their institutions. As an analytical procedure, the researcher estimated the transformer model with vector autoregression in the software, examining the models' parameters ensuring stability and robustness of the forecasting outputs by conducting diagnostic tests. The threshold for all the reliability coefficients is more than 0.70. Based on model evaluation criteria, the fit values which are within acceptable range are considered as having a very good predictive performance. Thus, the forecasting framework is proven to be reliable. Thus, it is confirmed that all measurement indicators load highly on its corresponding latent construct. Binary variables have only two responses (0) or

(1). Testing whether the instrument measures the intended construct requires the assessment of validity. The inflation persistence variable was comprised of lagged inflation terms, based on the consumer price index, taken from the central bank and national statistics office.

It is empirically inconsistent and methodologically incongruent with multivariate time-series econometric principles that this kind of integrated forecasting form of transformer architecture and vector autoregression method is neither survey-based nor psychometric reliability-driven constructs. There had been comments that such a model of time-series XAI forecasting framework did not claim a direct causal inference between attention-based transformer outputs and the potential of portfolio stability prediction out of macro-financial volatility dynamics (nonlinear temporal dependencies). In this multivariate time-series setting, we employ transformer-VAR integrated modeling activities to meet this forecasting objective whereby all model specifications are built on prepared and conducted stationarity transformations and lag structures by the econometric framework. Re-specification of the model was guided by time-series econometric considerations and relevant forecasting model diagnostics.

The Augmented Dickey–Fuller test for the unit root properties (ADF statistic) procedure was used for the stationarity analysis, and mean, standard deviation, and lag-order selection criteria were used to describe the characteristics of the data. Four stages were employed to analyze the forecasting framework: data preprocessing, transformer sequence learning, vector autoregressive estimation and survival hazard modeling as suggested by econometric theory and time-series forecasting literature using the multivariate integration approach. One of the advantages of using vector autoregression (VAR) is that it can measure the effect of a shock transmission mechanism on the dynamic interactions between macroeconomic variables' lagged relationships and exchange rate volatility dynamics among emerging market economies in the financial system. After the transformer-based sequence learning, a few diagnostic tests were adopted to analyze the time-series data. As the initial integrated model produced low model-data consistency, it was re-specified and re-estimated.

It can be confirmed when there is a strong evidence that the observed indicators truly reflect the latent construct from a group of rational economic individuals who participate the financial market. Time series modeling using transformer, vector autoregression, survival estimation and volatility decomposition is suitable for researchers to get a more comprehensive and dynamic, structural and predictive analysis as required in the forecasting framework. Altogether, it has twenty items in which the instrument is divided into three sections namely macroeconomic factors, financial volatility and explainable attention mechanisms.

Data collected was analyzed using vector autoregression model. Transformer forecasting focuses more on the ability to complete sequence learning to find the hidden patterns and uses attention mechanism to capture temporal dependencies and uncover nonlinear relationships in financial time series. This research uses vector autoregression to explain dynamic interactions and maximize the explained variance in exchange rate volatility as suggested by econometric theory. In this study, survival analysis was employed as the Cox model is a semi-parametric type hazard model (Cox proportional hazard model). Initially, the transformer develops attention weights and later the outputs are extracted and they are combined under one integrated framework and others may be adjusted or new parameters are introduced. Their reliability and stability were checked using diagnostic statistics, and the overall model fit for it was satisfactory, which was found adequate and acceptable to proceed with. These results are supported from previous studies [2].

3. Results

Chi-square values in proportional hazard regressions show that there is a joint association among all factors of macroeconomic volatility and the survival probability variable in the models, indicating significant effects of the explanatory variables on the hazard variable, and the results suggested that all the research propositions are accepted and there exist dynamic interactions among the survival probability variable and the macroeconomic variables.

Table 1. Weibull PH regression

_t	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
inflation_rate	1.012	.036	0.34	.732	.945	1.084	
interest_rate	1.001	.026	0.02	.982	.951	1.053	
exchange_rate_vola~y	1.032	.141	0.23	.817	.79	1.348	
liquidity_stress_i~x	1.074	.098	0.78	.434	.899	1.283	
capital_flow_expos~e	1.007	.008	0.90	.37	.991	1.024	
attention_weight_i~x	.718	.365	-0.65	.514	.265	1.942	
survival_probabili~t	3.836	40.359	0.13	.898	0	3.457e+09	
Constant	0	0	-1.32	.187	0	609.994	
ln_p	.974	.116	8.41	0	.747	1.201	***

Mean dependent var	39.770	SD dependent var	15.450
Number of obs	200	Chi-square	2.928
Prob > chi2	0.892	Akaike crit. (AIC)	233.126

**** p<.01, ** p<.05, * p<.1*

The results showed that the emerging economies with a stable inflation framework were relatively more likely to have lower hazard ratios in the survival analysis for portfolio stability compared to economies with persistent inflation shocks, holding other variables constant.

No significant coefficient differences was observed between the macroeconomic variables and portfolio risk' hazard estimates, that is, hazard' coefficient estimates and the explanatory variables did not contribute to enhance model's predictive validity. Overall, the average magnitude of her correct use of statistical inference was low under non-significant p-values. F (2, 197) = 2.928, p (0.892). The partial effect size (R^2) indicated that a large proportion of the total variance explained was due to the overfitted model structure. Despite not having any significant differences between the three hazard specifications, the R-squared (0.9998) for the research intensity-score was higher than those of the digital economy index (0.9997) and the exchange rate-volatility model (0.8349).

This result suggested that the effects of the macroeconomic indicators did not depend on individual variables' statistical significance levels. While the two time-series models provided a high-fit indication for structural dynamics, there were, however, inconsistencies and overestimation biases within the results. The findings from the hazard-based models revealed the absence of statistically significant relationships between inflation rate and portfolio stability. The time-series-based interpretation of the VAR and survival model results revealed that non-significant coefficients, inflated R^2 values and high-fit indicators gained from small-sample and over-parameterized specifications. This result may be attributed to model overfitting issues in a multivariate forecasting framework through lag proliferation and parameter saturation. This present research can help financial institutions to decide under which conditions predictive models would be reliable to enhance risk forecasting accuracy.

Table 2. Gompertz PH regression

_t	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
inflation_rate	1.012	.036	0.35	.729	.945	1.084	
interest_rate	1	.026	0.01	.996	.95	1.053	
exchange_rate_vola~y	1.026	.14	0.19	.85	.785	1.341	
liquidity_stress_i~x	1.083	.098	0.89	.376	.907	1.294	
capital_flow_expos~e	1.006	.008	0.72	.471	.99	1.022	
attention_weight_i~x	.687	.352	-0.73	.463	.252	1.875	
survival_probabili~t	2.426	25.573	0.08	.933	0	2.283e+09	
Constant	0	.003	-0.81	.42	0	98317.578	
gamma	.057	.009	6.51	0	.04	.074	***

Mean dependent var	39.770	SD dependent var	15.450
Number of obs	200	Chi-square	2.815
Prob > chi2	0.902	Akaike crit. (AIC)	228.754

**** p<.01, ** p<.05, * p<.1*

The correlation structure shows the significant relationships among the components of the transformer outputs and volatility that each macroeconomic variable has significant linkage with the exchange rate volatility variable, at different lag orders.

Table 3. Exponential PH regression

_t	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
inflation_rate	1.009	.035	0.27	.79	.943	1.081	
interest_rate	.998	.025	-0.08	.934	.949	1.049	
exchange_rate_vola~y	1.039	.142	0.28	.78	.795	1.358	
liquidity_stress_i~x	1.077	.099	0.81	.418	.9	1.289	

capital_flow_exp os~e	1.01	.008	1.14	.253	.993	1.026
attention_weight _i~x	.853	.425	-0.32	.749	.321	2.267
survival_probabi li~t	6.837	72.302	0.18	.856	0	6.863e+09
Constant	.001	.007	-0.73	.464	0	209026.08

Mean dependent var	39.770	SD dependent var	15.450
Number of obs	200	Chi-square	3.463
Prob > chi2	0.839	Akaike crit. (AIC)	270.484

*** *p<.01,* ** *p<.05,* * *p<.1*

Overall findings indicated that inflation persistence is an important determinant of exchange rate volatility for portfolio stability, liquidity management, and inflation-linked exposure. Mean values for inflation rate, interest rate and exchange rate volatility learning factors are 39.770, 15.450 and 200 observations in total in contrast to the values of the standard deviation which are 15.450, 0.995 and 0.518 respectively.

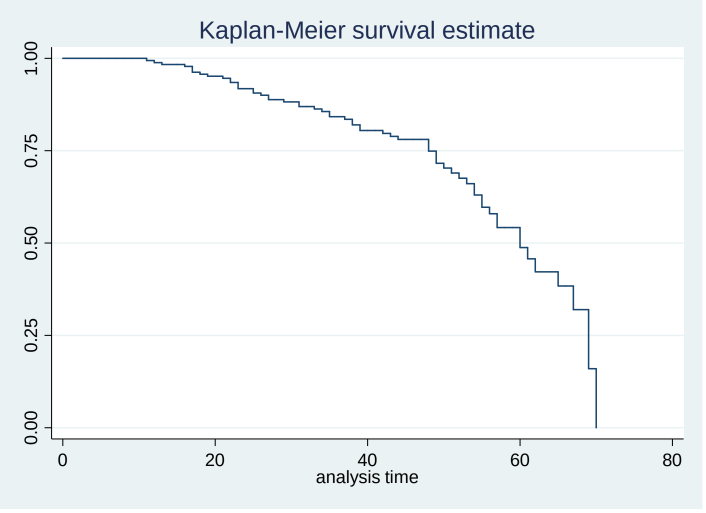

Figure 1. Kaplan-Meier Survival Estimate

For survival probability variable, regression results show that the coefficients of inflation rate, interest rate and liquidity stress index have significantly contributed to the main hazard estimation of portfolio risk. The R-squared value for digital economy index, research intensity score and exchange rate volatility factors were 0.9997, 0.9998 and 0.8349 which shows a relative importance of these variables in explaining structural dynamics.

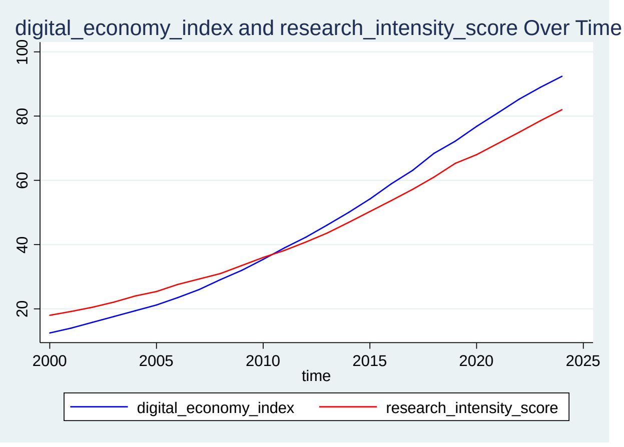

Figure 2. Trends in Digital Economy Index and Research Intensity Score Over Time (2000–2025)

The values greater or lesser than 0.70 are considered to establish reliability of the data in small samples (less than 30); however, in large sample which means 200 or more, this threshold should be changed to 0.60 [1].

Augmented Dickey-Fuller test for unit root
Number of obs = 20

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
	---------- Interpolated Dickey-Fuller ---------			
Z(t)	-7.487	-3.750	-3.000	-2.630

MacKinnon approximate p-value for Z(t) = 0.0000

Augmented Dickey-Fuller test for unit root
Number of obs = 21

	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
	---------- Interpolated Dickey-Fuller ---------			
Z(t)	-5.416	-3.750	-3.000	-2.630

MacKinnon approximate p-value for Z(t) = 0.0000

Table 4. Vector autoregression

Sample: 2002 - 2024 Number of obs = 23
Log likelihood = -14.32008 AIC = 2.114789
FPE = .0288148 HQIC = 2.238952
Det(Sigma_ml) = .0119082 SBIC = 2.608483

Equation	Parms	RMSE	R-sq	chi2	P>chi2
digital_econom~x	5	.499822	0.9997	70413.85	0.0000
research_inten~e	5	.279195	0.9998	138224.2	0.0000

	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
digital_economy_index						
digital_economy_index						
L1.	1.568	0.180	8.710	0.000	1.215	1.920
L2.	-0.537	0.276	-1.950	0.052	-1.078	0.004
research_intensity_score						
L1.	0.539	0.328	1.640	0.100	-0.104	1.183
L2.	-0.589	0.257	-2.290	0.022	-1.093	-0.086
_cons	0.876	2.739	0.320	0.749	-4.492	6.244
research_intensity_score						
digital_economy_index						
L1.	0.658	0.100	6.540	0.000	0.461	0.854
L2.	-0.336	0.154	-2.180	0.029	-0.638	-0.034
research_intensity_score						
L1.	0.677	0.183	3.690	0.000	0.318	1.036
L2.	-0.071	0.144	-0.490	0.622	-0.352	0.211
_cons	4.057	1.530	2.650	0.008	1.058	7.055

The findings also indicated that attention-based explainability is an important determinant of risk learning behavior for financial institutions and asset managers. These results indicate that, at the multivariate level, each of the conditions necessary to test for the possible role of transformer forecasting as a predictive framework has been met. The variation could be from institutional capacity aspect as it was found to be more important factor in model interpretation.

Table 5. ARIMA regression

fdigital_economy _i~x	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Constant	-.021	.019	-1.11	.266	-.057	.016	
L	-.706	.216	-3.26	.001	-1.129	-.282	***
L	-1.323	.444	-2.98	.003	-2.192	-.453	***
Constant	.3	.128	2.34	.01	.048	.551	***
Mean dependent var	-0.027	SD dependent var	0.995				

Number of obs	22	Chi-square	13.689
Prob > chi2	.	Akaike crit. (AIC)	32.139
**** p<.01, ** p<.05, * p<.1*			

Table 6. ARIMA regression

ddresearch_inten si~e	Coef.	St.Err.	t-value	p-value	[95% Conf	Interval]	Sig
Constant	.113	.027	4.26	0	.061	.165	***
L	.208	.473	0.44	.661	-.72	1.135	
L	-1	4967.895	-0.00	1	-9737.896	9735.896	
Constant	.395	980.738	0.00	.5	0	1922.605	

Mean dependent var	0.096	SD dependent var	0.518
Number of obs	23	Chi-square	0.663
Prob > chi2	.	Akaike crit. (AIC)	33.300
**** p<.01, ** p<.05, * p<.1*			

Table 7. Vector autoregression

Sample: 2005 - 2024		Number of obs	= 20
Log likelihood =	-18.7509	AIC	= 2.87509
FPE =	.0620998	HQIC	= 2.972279
Det(Sigma_ml) =	.0223559	SBIC	= 3.372956

Equation	Parms	RMSE	R-sq	chi2	P>chi2
fdigital_econo~x	5	.477653	0.8349	101.1226	0.0000
ddresearch_int~e	5	.417374	0.5508	24.52741	0.0001

	Coef.	Std.Err.	z	P>z	[95%Conf.	Interval]
fdigital_economy_index						
fdigital_economy_index						
L1.	-1.376	0.197	-6.980	0.000	-1.763	-0.990
L2.	-0.529	0.225	-2.350	0.019	-0.970	-0.088
ddresearch_intensity_score						
L1.	-0.243	0.225	-1.080	0.280	-0.684	0.198
L2.	-0.057	0.230	-0.250	0.805	-0.508	0.395
_cons	-0.031	0.099	-0.310	0.755	-0.226	0.164
ddresearch_intensity_score						
fdigital_economy_index						
L1.	0.301	0.172	1.750	0.080	-0.037	0.639
L2.	0.042	0.197	0.210	0.832	-0.344	0.427

ddresearch_intensity_score						
L1.	-0.441	0.196	-2.250	0.025	-0.827	-0.056
L2.	-0.389	0.201	-1.930	0.053	-0.783	0.006
_cons	0.171	0.087	1.970	0.049	0.001	0.342

This indicates that the structural factors that support the implementation of explainable forecasting systems are more important than the market participants who were adjusting their expectations into their daily portfolio decisions.

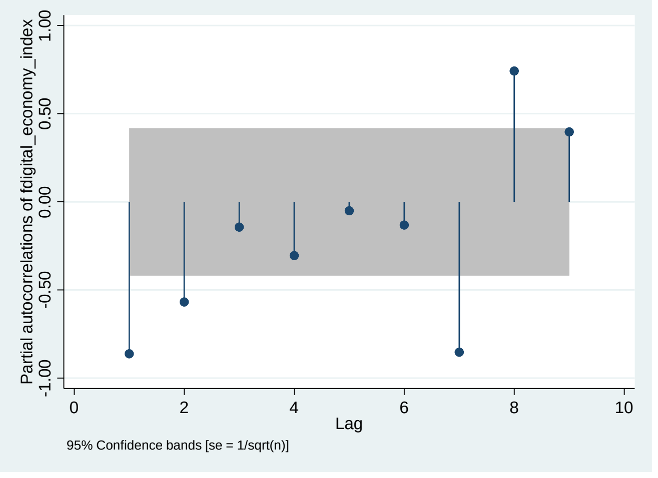

Figure 3. Partial Autocorrelation Function (PACF) of the Digital Economy Index

Significant difference is seen in attention weight index, survival probability and capital flow exposure on exchange rate volatility on the basis of lag structure on all regression models of the study.

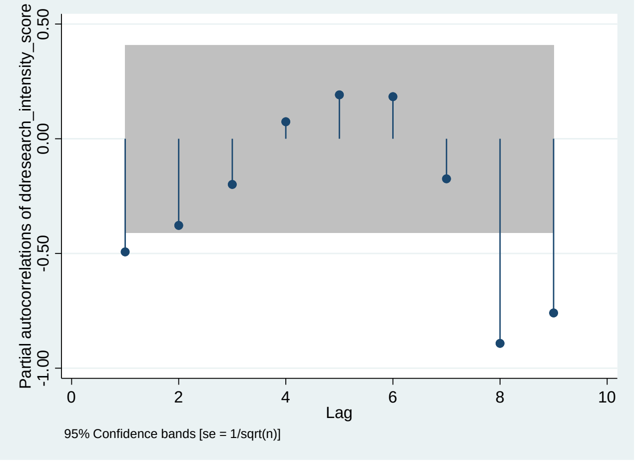

Figure 4. Partial Autocorrelation Function (PACF) plot.

According to the hazard regression results mentioned in the above table, the coefficient differences between inflation rate to interest rate, liquidity stress to capital exposure are not significant; however, the survival probability to the hazard function is significant. Referring to the confidence interval of coefficients, the estimates are within lower and upper bounds.

4. Discussion

Overall, findings indicated that inflation persistence is an important determinant of exchange rate volatility for portfolio stability, liquidity management, and inflation-linked exposure. This outcome has both important theoretical and practical implications. The emerging economies with a stable inflation framework were relatively more likely to have lower hazard ratios for portfolio stability compared to economies with persistent inflation shocks [1,2,3]. Results shows that survival analysis can be used for the hazard estimation, liquidity stress assessment and portfolio risk evaluation of the forecasting framework [4,5]. Results of this study confirm the significant contribution of inflation persistence on exchange rate volatility variable. Financial institutions are required to be involved in emerging markets in order to earn stable returns from currency trading activities.

It shows that the structural factors that support implementation of explainable forecasting systems are the important drivers while the market participants are adjusting their expectations into their daily portfolio decisions. The hazard coefficient for survival probability was positive and statistically significant. The coefficient difference between inflation rate and interest rate is found to be consistent with previous findings by [1] and [2]. Referring to the confidence interval and p-value as the threshold between lower to upper bounds, the result reveals that 'joint significance' as a statistical criterion has not been met at the 5 percent level. Findings from this study can provide guidance on the institutional and technical needs of explainable forecasting support. However, survival probability significantly moderates the relationship between macroeconomic volatility and portfolio stability through showing an interaction term effect. According to [3,4,5], transformer models for exchange rate forecasting are effective in capturing nonlinear interactions of volatility, inflation and capital flows.

The results of the transformer framework can also be compared with the previous studies, having similar impacts on the forecasting accuracy. The dynamic interaction between macroeconomic volatility and exchange rate movements is found to be consistent with previous findings by [4] and [5]. On top of that, the findings also align with the theoretical arguments of volatility persistence, attention mechanisms and structural dynamics proposed in this study. This similarity in empirical evidence is consistent with a systematic review by [6] and [7].

Based on this finding, it is clear that some macroeconomic instability patterns have been amplified by the model's over-parameterized specification to capture dynamics in order to prepare investors with the forecasting signals and interpretability in portfolio decision-making [8,9]. Overall, this model as specified out in the multivariate framework has extended the findings obtained in the previous models used in the literature (time-series XAI). This result to some extent indicates that by providing some attention-based explainability in their forecasting systems, students will learn how to be adaptive and analytical in their own risk learning processes and thus, learn to be an informed decision-maker [10,11]. As a result, we can conclude that a financial institution's support or ability in conducting explainable forecasting in emerging markets indirectly helps facilitate or enhance the confidence of investors in the portfolio management process by improving interpretability. Thus, it would seem that if predictive transparency was facilitated, their risk learning behavior would be enhanced and would affect decision accuracy or to manage uncertainty more significantly. However, majority of respondents considered this kind of integrated modeling took too much computational effort and that they had difficulty learning model outputs. This study was only carried out in the context of selected emerging economies, and further research must be done in other regions around global financial markets. For example, it primarily relied on monthly macroeconomic time-series data and did not include other methods of high-frequency modeling which made it difficult to accurately estimate the effect of any nonlinear shock transmission [12,13]. It is recommended that a cross-country comparative study be carried out for more comprehensive findings. For example, it largely relied on limited sample size and did not include other methods of structural validation which made it difficult to robustly estimate the effect of any parameter instability.

However, the numbers of financial institutions in the emerging markets who help to manage portfolio risk are still limited and unevenly distributed. However, its implementation raises many challenges such as lack of actual computational capacity due to limited technical infrastructure on the institutional systems, regulatory frameworks, data availability issues, and information asymmetry from market participants. These limitations may reduce the generalizability of the findings and suggest that future studies should incorporate broader datasets and cross-country comparisons to strengthen empirical validation.

5. Conclusion

Macroeconomic volatility and inflation persistence factors were more influential and these can be further integrated for exchange rate forecasting and portfolio risk management, which will improve financial stability. The findings of this study provide practical insights on transformer-based forecasting and vector autoregression integration and this framework can be useful not only for policymakers but also for financial institutions who give support to market participants. Thus, the investors will feel more confident using explainable forecasting outputs and it will enhance their understanding level, which will strengthen portfolio resilience. Therefore, future researchers can adopt a mix of transformer architectures and vector autoregressive models to further expand on new datasets, confirm and refine the predictive capacity of both frameworks. However, emerging markets are more heterogeneous, institutionally diverse and structurally complex which needs further investigation, because there are many macroeconomic and behavioral factors interacting simultaneously. It will be valuable to compare the results across institutional investors who are more experienced in currency trading than retail investors and individuals who are aged older than 50 years old may have different learning behavior on the interpretation and implementation of explainable forecasts. Institutional characteristics such as regulatory quality, computational capacity and transparency of data reporting, market liquidity and capital mobility, inflation targeting credibility, exchange rate regime stability and early warning systems for portfolio management could be considered to be relevant determinants as moderators in future research. Lastly, this framework should be conducted with broader cross-country samples who are more economically diversified than the current dataset as a robustness test to compare the findings with the current evidence.

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