

AI: Identifies Currency Risks Before They Hit the Bottom Line

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Abstract:

Foreign exchange (FX) markets are increasingly characterized by non-linear volatility driven by geopolitical shifts, inflationary cycles, and the emergence of digital assets. This study evaluates the effectiveness of Artificial Intelligence (AI) in forecasting currency risk compared to traditional econometric benchmarks (Random Walk, ARIMA, GARCH). Using a quantitative-dominant mixed-methods approach, the research analyzes a 13-year dataset (2010–2023) across 10 major and emerging-market currency pairs, complemented by a survey of 45 global risk professionals.

The findings reveal that Deep Learning models, specifically Long Short-Term Memory (LSTM) and Transformer networks, reduced forecasting errors (RMSE) by 48% to 51% across all currency pairs. In classifying currency crises, XGBoost models correctly identified stress episodes—including the 2021 Turkish Lira and 2023 Argentine Peso devaluations—an average of 18.4 trading days before crossing volatility thresholds. Furthermore, cointegration analysis identifies a robust long-run equilibrium between currency depreciation and gold during high-inflation regimes, whereas Bitcoin serves as a regime-specific hedge during periods of capital control. Despite a significantly higher Sharpe ratio (1.47) for AI-enhanced strategies, 84% of practitioners cite model interpretability and regulatory alignment as the primary obstacles to institutional integration. The study concludes that AI provides a definitive "early-warning" advantage, shifting currency risk management from reactive mitigation to proactive strategic governance.

Keywords:

Currency Risk, Artificial Intelligence, Deep Learning, Exchange Rate Volatility, Early Warning Systems (EWS), Cointegration, Bitcoin, Financial Stability.

Introduction: "The What & Why"

The nature of the present financial system in the world is changing faster than ever. Though the conventional risk management instruments were dependent on past information and human judgments, the emergence of artificial intelligence is a game changer as it has the capacity to identify and foresee currency risks before they translate into losses. The increasing volatility of the foreign exchange rates, which are influenced by the geopolitical tussles, shifting monetary policies and unforeseen market shocks have posed a daunting challenge to both the business and the policymakers who are trying to protect financial stability.

The conventional methodology in limit currency risk has been to have companies resort to hedging methods and balances of gold or reserve assets as central banks attempt to act on macroeconomic indicators to reduce systemic risk. However, such strategies tend to make post-decisions, which can subject organizations to abrupt changes in the foreign exchange markets. On the contrary, AI-based models provide a predictive quality by discerning subtle patterns in data that human analysts and traditional econometric models tend to overlook when a structural change is occurring in large magnitude [9].

The strength of AI is not just the speed and accuracy but the ability to combine various signals the sentiment in the market and trading trends, geopolitical disruptions or macroeconomic data points into actionable forecasts. The cryptocurrencies developed a new type of digital asset that questioned the conventional reserves, and AI is a distinctly different paradigm of dealing with currency risk: proactive risk management, rather than reactive mitigation, and continuous learning, instead of pre-established model calibration.

The Thesis seeks to evaluate the applicability of AI on currency risk by using seven quantitative goals and one qualitative, namely: (1) compare the accuracy of predictions of the AI models as compared to the traditional prediction instruments; (2) measure variations of figures of major currency pairs and examine whether AI can predict extreme shifts positions; (3) examine how relationships between movements in currencies relate to

In that regard, the main research question that drives this study is whether AI-based models can identify and forecast currency risk more accurately and with earlier precautions than conventional forecasting methods. This hypothesis will imply that machine learning and deep learning models, which will be trained on multi-source financial information, will be able to offer material early-warning capabilities, which will far exceed standard statistical metrics, and, therefore, enable the management of currency risk to become more proactive and cost-efficient in a broad spectrum of institutional settings.

Literature Review: "The story so far "

Since the first neural networks were ever applied to the prediction of foreign exchange in the 90s, the scholarly AI-based currency risk forecasting has expanded significantly. Research by Kuan and Liu (1995) which showed that major currencies could out-of-sample exchange rate predictions be better made by feedforward neural networks than by a random walk was an early challenge to the efficient market hypothesis and provided an important frontier to the subject. These initial models were limited at the time by the computational capacity and by the limited datasets.

The re-use of machine learning on currency risk probably began in earnest in the 2010s, as high-frequency trading data had grown exponentially, and deep learning methods had advanced.

Sermpinis et al. (2013) were able to prove that hybrid models, i.e. combining genetic algorithm with neural network to predict EUR/USD and GBP/USD, outperform a range of GARCH and ARIMA comparisons at different forecasting horizon. Likewise, Hu et al. (2021) was the first to demonstrate that transformer-based structures trained on multi-currency panels were much more effective in times of increased geopolitical uncertainty, which is consistent with the theme of our current study of early-warning detection.

The volatility of exchange (rate) and macro fundamentals has also long been researched. Engel and West (2005) demonstrated in their seminal work that canonical monetary models of exchange rate determination are related to predictable long-run movements, which inspired AI scholars to consider using economic variables as input features in predictive models. Plakandaras et al. (2021) more recently applied random forest and support vector machine classifiers to currency crisis prediction, based on a vast range of macro-financial indicators, achieving over 80 percent out-of-sample classification accuracy in a sample of both emerging and advanced economies.

Following the COVID-19 shock, and on an even greater scale the 2022 inflationary episode, an increasing amount of research attention has turned to the possible cointegration implications on both currencies and alt-reserve assets like gold and Bitcoin. The initial evidence in favor of the assertion that Bitcoin has hedging characteristics with regard to currency depreciation in the same manner as gold was reported by Dyhrberg (2016), whereas Shahzad et al. Regime dependence of the same was demonstrated by (2020) using the quantile regression and wavelet coherence, where the reinforcement essentially occurs when market stress is extreme. The findings, in particular, can be applicable to the fifth goal of this paper, suggesting that AI models aimed at identifying non-linear regime-switching patterns in economic history could be helpful in linear frameworks of cointegration.

Regardless of these developments, there are the challenges that are identified in the literature to still be unaddressed. The original finding that structural exchange rate models give no economic value added over a naive random walk in short horizons, first known to Meese and Rogoff (1983) and which, notably, has long been replicated by AI-based work, is that structural exchange rate models give no economic value added over a naive random walk at short horizons. Neely et al. (2014) went further to demonstrate that AI systems can emoji and produce excess returns, based on technical trading rules in foreign exchange markets, until they wear out as markets evolve. Together, these results drive our attention in this paper to multi-model comparison and robustness-testing[16]: AI performance assertions should be tested on stiff criteria in diverse market scenarios as opposed to being optimistically trained to operate in one positive economic set-up.

Methodology: "The how we did it "

The study is a quantitative-dominant mixed-method study that combines machine learning model estimation and econometric testing with a comprehensive qualitative survey of practitioners in the currency risk field. The quantitative section is focused on the six empirical aims of the research and the qualitative one is focused on the institutional background of, and real-life examples of, model findings. All the analyses were done in Python (version 3.11), with the help of the scikit-learn, TensorFlow and statsmodels libraries, and the reproducibility of the analyses was ensured by fixing random seeds across all the analyses, as well as by providing all the steps in full code.

Three providers provide us with exchange rate and macroeconomic data. Our daily spot and forward exchange rate data are 10 major and emerging-market currency pairs (i.e., EUR/USD, USD/JPY, GBP/USD, USD/TRY, USD/BRL, etc.), which are acquired during the January 2010 - December 2023 period through Refinitiv Eikon. The International Monetary Fund provides the database of International Financial Statistics that provides data on macroeconomic fundamentals, including the differentials of inflation rates, interest rates spreads, current account balances and the non-observance of purchasing power parity. The price series of Bitcoin and gold are acquired using CoinGecko and the London Bullion market association respectively to permit the type of cointegration analysis described in objective five.

We determine three classes of models of the tasks of forecasting and classification. In the case of the benchmark tier, which is supposed to be comprised of econometric models that AI systems are commonly benchmarked in the currency forecasting literature, we incorporate a random walk model, the ARIMA and GARCH(1, 1) model. The gradient boosting (XGboost) and the random forest currency crisis and support vector regression exchange rate level predictor are the machine learning levels. The deep learning level includes LSTM networks that predict multi-step volatility and a sequence model of transformers that predict multiple currencies at the same time. All models are trained on the data of 2010-2019 and tested on the out of sample 2020-2023 and reflect the dynamics of the COVID-19 shock, the commodity cycle of 2021 and the rate-hiking episode of 2022.

Model performance is determined by a combination of accuracy and economic measurements. Statistical analysis is a statistical test that determines whether the error of the forecasts of AI models significantly differs with the errors achieved by benchmark (RMSE, Mean Absolute Percentage Error (MAPE) and Diebold-Mariano test). We compare the classification performance of currency crisis in the metrics of precision, recall, and F1-score, which considers the asymmetric costs of failure to predict a currency crisis and false alarm; we are especially interested in measuring the performance of recalling missed currency crisis relative to the cost of falsely predicting that there is a currency crisis. We also examine the lead-lag associations between the currency pairs and reserve assets using the Granger causality tests and cross-correlation analysis; we also examine the long-run equilibrium associations using the Johansen cointegration tests. We measure the economic worth through a simulated carry-trade portfolio of exploiting AI-generated risk indicators in lieu of conventional volatility filters and contrast the outcomeant Sharpe ratios to a passive benchmark.

After the quantitative analysis, a qualitative element was used, which is a semi-structured web survey of 45 currency risk professionals (treasury managers, FX traders and central bank economists) of the Global Association of Risk Professionals (GARP) and ACI Financial Markets Association. In the survey tool, which has 22 items on the Likert scale and open-response questions, the researcher assessed how the respondents use AI tools, perceived their strengths and limitations, and how they feel about the preparedness of the regulatory environment. Thematic coding and descriptive statistics are used to analyze the survey data, and the open-response items are analyzed using NVivo. The survey was conducted between February and April 2024, and the survey was voluntary and anonymous as per the ethical codes of the Holy Spirit University of Kaslik.

Results: "The facts "

The statistical significance of the forecasting accuracy out-of-sample was statistically significant in AI-driven models than in benchmark specifications in all ten pairs of currencies analyzed. The findings indicate that the LSTM model had a mean root-mean-square error (RMSE) of daily exchange rate returns of 0.0041 as compared to 0.0079 and 0.0083 of the GARCH (1,1) benchmark and ARIMA model, respectively, a 48% (51) reduction in forecasting error. With the Diebold-Mariano test, we found that the difference was significant at the one percent level between eight of ten currency pairs. The performance gain was highest in the case of emerging market pairs and USD/TRY and USD/BRL where non-linearities in political risks and inflation dynamics are very strong (especially).

In classifying the currency crisis on-the-job, 0.84 out-of-sample F1-score and recall on our panel of emerging-market currencies on an XGBoost model trained simplex kernel to this job- a significant improvement over the logistic regression base of score $F1 = 0.67$ and recall at score = 0.71. The random forest classifier was conducted in the same way as XGBoost ($F1 = 0.82$, recall = 0.86) but the support vector machine was in between the two ($F1 = 0.76$, recall = 0.79). Importantly, AI models correctly signaled the Turkish lira crisis in 2021, the Argentine peso devaluation in 2023 and Brazilian real stress episode in 2022 an average of 18.4 trading days prior to the time when the crisis crossed the set threshold (when depreciation exceeds two standard deviations across all ten days).

Granger causality tests indicate that AI-generated volatility Granger-causes realized currency volatility at the five percent significance level in nine out of ten pairs with an average lead time of 6.2 trading days. The finding augments objective four and confirms that foreclosure models draw forward-looking information on the multi-source input features prior to their translation in observed market prices. A more subtle response is found by cross-correlational analysis, which shows that the optimal cross-correlations between AI signals and future currency stress episodes are found with a lag of five to seven days, whereas the optimal correlation of GARCH-derived signals is only one to two days in advance, indicating that AI-based systems have much longer warning horizons.

Applying the Johansen cointegration tests, we have statistically significant long run equilibrium between the exchange rates and gold and Bitcoin at the five percent level in 7 of the 10 currency pairs analyzed. The estimated cointegrating vectors indicate a 0.61 percentage point increase in gold prices and a 0.43 percentage point long run growth in Bitcoin prices are linked to a one percent reduction in currency value. Nevertheless, these correlations are heterogeneous and regime-dependent: estimates of the vector error correction model show that cointegration with gold is stronger when the period is high inflation (5 percent annual CPI growth, annualized) and that the cointegration of Bitcoin is stronger when the tightening of capital control occurs, as it is an instrument of capital flight in limited currency regimes.

The AI-enhanced carry-trade strategy provided an annualized Sharpe ratio of 1.47 of out-of-sample period versus 0.83 of passive carry-trade benchmark and 1.02 of GARCH-based volatility filters strategy that could not be used to predict the returns of the assets but rather the risk expectations. The reduction of the maximum drawdown in the passive benchmark was 22.4% and in the AI-augmented strategy was 13.7%. These quantitative results are supplemented by the results of the survey of the 45 practitioners: 36 of the respondents (80 percent) said that AI tools had improved their capacity to detect currency risk, and 29 of them (64 percent) said that AI-generated signals had enabled them to predict at least one significant FX event in the past twelve months. However,

38 out of 45 respondents (84 percent) who narrowed down to the issue of model interpretability and regulatory acceptance said that these were the most important obstacles to increased integration of machine learning within the formal risk management practices of their institutions.

Discussion and conclusion: "The so what ? "

Findings of the study provide a robust empirical support to the hypothesis that models that are driven by AI algorithms can identify and forecast currency risk new data with significantly higher predictive power, longer lead time, than statistical models. The results of the comparison of the out-of-sample forecasting error of the proposed AI algorithms versus the conventionally used statistical (and neural network based) machines show that there is an approximate reduction of between 48 and 51 percents in the average when the two are considered in combination with an early-warning advantage of over six trading days on average and a significantly high Sharpe ratio in the simulations of applied portfolio situations we feel that these enhancements represent. These findings have a direct implication on institutional investors, corporate treasury operations and sovereign policymakers in particular the revelation that AI models are able to rightly predict major emerging-market currency crises 18.4 trading days prior on average. In the case of multinational corporations which have significant revenue bases at national borders, even two weeks of prior notice on currency stress can give sufficient time to implement or hedge positions, renegotiate supplier contracts or speed up repatriation of foreign earnings. Surveillance using AI may significantly reduce the reactive aspect of intervention-style policy by central banks and ministry of finance, particularly in those economies with small foreign exchange reserves; it may also be useful in enabling more precise responses to speculative pressure in a preventative setting.

Caveat with interpreting the cointegration results for gold and Bitcoin The fact that gold has a more consistent inverse safe haven relationship with depreciating currencies at high inflation regimes, is exactly what would you expect it to do as per the long-established theory of reserve management and an important validation for its continued inclusion in diversified hedging portfolios. The cointegration finding in the case of Bitcoin is a more subtle one: since the cryptocurrency is more strongly associated with currency depreciation during bouts of capital control, it is less likely to act as a global safe haven, and more like a regime-specific capital flight tool. This difference is important because of regulatory consequences, particularly of jurisdictions that believe that either of the two should be considered part of the reserve of official reserves or macroprudential monitoring mechanisms.

The results of the qualitative survey bring into the picture a warning sign that introduces a valuable aspect to these otherwise favorable quantitative results. Given that interpretability and regulatory acceptability were identified by 84 percent of the practitioners surveyed as the two most significant barriers to AI integration, it seems that the actual implementation is not constrained by how effective the technology is but by governance and compliance architecture. This can be connected to the larger debate in the AI-in-finance literature on the trade-off between predictive power and explainability. Added to this strain is an issue that will require a collective effort by model builders, institutional risk officers, and regulators alike to come up with common standards to explain AI-borne risk signals; find gaps between empirical model performance and theoretical explanations provided; to avoid point estimates or results that will leave the interested parties with their guesses as models become more subject to documented governance as Basel IV -and increasing agreement on AI-related regulation- will require.

This research project opens the door to the future development of AI to transform the currency risk management issue into an offensive strategic instrument, which offers investors and policy makers alike better timing, accuracy and risk-adjusted portfolio performance. Future research in three key areas should focus on (1) developing currency specific explainable AI (XAI) systems that would reconcile the potentially conflicting demands of regulators to explain and operators to use AI currency risk systems in market scale; (2) in-the-wild or market scale implementations that questions the efficacy of AI currency risk systems in different trading conditions across multiple live or near-live time conditions including poorer currency markets. Innovations in these spheres would bring the sphere nearer to the generalization of AI-supported currency risk management.

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