

Optimal timing in foreign exchange markets: The role of economic fundamentals and market connectedness

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Abstract. This paper develops an integrative methodology to determine the optimal execution time in the foreign exchange markets using mixed-data sampling (MIDAS) regression technique. The MIDAS technique aims to integrate low-frequency macroeconomic indicators with high-frequency market data. The paper utilizes daily exchange rates for seven major currency pairs (CAD/USD, CNY/USD, CDF/USD, EUR/USD, JPY/USD, ZAR/USD, and NGN/USD), covering a range of developing and developed economies. MIDAS regression models that incorporate annualized GDP growth rates and annualized inflation differentials were found to perform significantly better than autoregressive benchmarks, and achieved substantially higher R-squared values, specifically for emerging market currencies. Structural break analyses identified 14 separate volatility regimes, with high-stress regimes having 1.67 times higher volatility. Time-varying parameter Vector Autoregression models showed strong interconnections among currency pairs in the foreign exchange markets, with the majority of forecast error variance resulting from spillover effects, namely, the influence of shocks in one currency pair on the volatility of others. Through backtesting of several execution rules, we found that a simple momentum-based rule produced the highest risk-adjusted returns, with an average annual Sharpe

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ratio of 2.37. In contrast, low volatility and low connectivity rules resulted in negative returns. These results provide new empirical evidence of the ability of macro fundamental indicators to predict future behavior in the foreign exchange markets, and illustrate the practical application of MIDAS-based execution time models in managing the risks associated with executing large scale transactions across structurally diverse economies.

Keywords: foreign exchange, execution timing, market connectedness, spillover networks, MIDAS, momentum strategy

JEL Classification: G11, G15, F31, C58

1. INTRODUCTION

The foreign exchange (FX) market represents one of the largest and most liquid financial markets in the world, with daily trading volumes exceeding \$6 trillion. For multinational corporations that settle invoices, institutional investors that manage their portfolios; and central banks that oversee reserve management, transaction timing in the FX market is anything but trivial. Because inefficient execution can lead to significant "implementation shortfall," even by hours, and subsequently negatively impact profitability and investment performance, the search for an optimal FX execution timing framework represents a pressing issue of both practical and academic significance.

One of the primary challenges associated with finding the optimal FX execution framework is the complexity of the FX market's information environment. Specifically, the FX market's prices reflect a wide variety of influences, including long-term economic fundamentals and short-term intraday order flows. Therefore, the FX market represents a very difficult-to-model environment.

Historically, researchers have employed two distinct approaches to addressing the modeling issues of the FX market. One approach, based on macroeconomic theory, has identified several relationships between the value of exchange rates and various macroeconomic variables, including inflation rates, interest rate differentials, and GDP growth (Taylor & Taylor, 2004). However, the empirical inability of these models to accurately forecast exchange rates outside of sample periods, particularly those related to short horizons, has been demonstrated to be a long-standing puzzle in the field of financial economics, since the early 1980s (Meese & Rogoff, 1983).

A second body of research has focused on the high frequency aspects of the FX market's microstructure, specifically examining how certain market variables, such as order flow, bid-ask spreads, and liquidity, contribute to price discovery (Evans & Lyons, 2002). While the models developed through this line of inquiry have been successful in explaining the intraday behavior of exchange rates, they typically operate in isolation from the low-frequency macroeconomic variables that underlies the behavior of exchange rates. This represents a significant research gap, in that there exists a disconnect between the low-frequency fundamentals that determine the overall direction of exchange rates, and the high-frequency execution strategies that are employed by traders to take advantage of opportunities that arise due to fluctuations in the values of currencies.

In addition, the increasing degree of globalization has created an environment in which no single currency operates independently. Rather, changes in one currency can rapidly spread to other currencies, creating a complex web of interconnected markets (Diebold & Yilmaz, 2014). While Diebold and Yilmaz (2014) provided a framework for understanding the dynamic interconnectedness of currencies, their work

primarily focused on identifying patterns of interconnectedness and did not provide guidance on how these patterns could be utilized to inform the development of execution strategies.

Most existing FX execution timing models either ignore the dynamic interdependencies between currencies, or assume a static network structure, which ignores the changing nature of market influence and contagion risk (Lee & Kim, 2023). Therefore, the objective of this study is to develop a comprehensive model of the FX market that addresses each of the above limitations.

We will accomplish this goal by employing a three stage research pipeline to integrate data collected from multiple sources. Through this pipeline, we will pose four specific research questions: (1) Do low frequency macroeconomic fundamentals contain incremental information that can help to improve the predictability of high frequency FX returns? (2) Are FX markets characterized by structural regimes, and if so, what are the differences in volatility dynamics and risk-return profiles between these states? (3) How does the intensity of interconnectedness and magnitude of spillovers between currencies evolve over time, especially during periods of market stress? (4) What is the underlying topological structure of the FX spillover network, and which currencies act as central nodes for transmitting and receiving shocks?

We will utilize a unique combination of advanced econometric methodologies to address each of these research questions. We will first employ mixed data sampling (MIDAS) regression techniques to formally test whether low-frequency macroeconomic data provides incremental predictive power for high-frequency daily returns. Next, we will utilize structural break analysis to identify distinct market regimes. Our core methodology will be a time-varying parameter vector autoregression (TVP-VAR) model, from which we will derive a dynamic total connectedness index and map the evolving network topology of FX markets. Critically, in a departure from previous studies, we will utilize these insights to operationalize them as a series of execution heuristics.

Overall, we find that FX markets represent a complex and dynamic environment. We present strong evidence that low-frequency macroeconomic fundamentals are important determinants of (high-frequency) daily returns, and that FX markets operate in multiple regimes with differing levels of volatility. We also demonstrate that the intensity of contagion between currencies is highly variable. Perhaps most importantly, we show that a simple momentum-based execution timing strategy produces the best and most consistent risk-adjusted returns compared to alternative heuristics. The most important evidence of the power of our MIDAS regression approach can be seen in our backtested results, which show that, as expected, a very simple strategy that uses just one factor, the momentum of price movement, will produce the best and most consistently high risk adjusted returns compared to all of the other heuristics we tested.

2. LITERATURE REVIEW

This study sits at the intersection of three discrete but complementary bodies of financial economics literature: forecasting of exchange rates, econometric modeling of mixed frequency data, and network analysis of financial markets. Our contribution comes from combining all three of these literatures to examine the practical issue of determining the optimal FX execution timing.

Forecasting of exchange rates is arguably one of the most persistent issues in international finance. The first wave of research in the area of exchange rate forecasting during the late 1970s and early 1980s centered around the use of structural models built upon macroeconomic fundamentals, such as monetary models and purchasing power parity. However, the influential article by Meese and Rogoff (1983) was a damper on this enthusiasm when they demonstrated that structural models generally failed to outperform a simple random walk in out-of-sample forecasting exercises. While this result was consistent across a vast body of subsequent research, it has led many to conclude that exchange rates are fundamentally disassociated from macroeconomic variables at short to medium horizons (Frankel & Rose, 1995).

Responding to the "disconnect puzzle," a second wave of research turned attention toward the microstructure of the market. Those who were proponents of this new perspective, such as Evans and Lyons (2002), posited that the market aggregates private information, and that this information is revealed through order flow. Utilizing high-frequency data on trades and quotes, Evans and Lyons (2002) discovered that order flow accounted for a large proportion of the movements in exchange rates at very short horizons. This stream of research has grown rapidly, and contemporary studies are utilizing ever finer-grained data to model the dynamics of liquidity, price impacts, and algorithmic trading behaviors (Smith, 2023; Chaboud et al., 2014). While the microstructure approach has been successful, it also has some drawbacks. Most notably, it typically does not account for the lower frequency macroeconomic factors that set expectations and cause larger scale market events. Our study adds to the microstructure literature by evaluating again the roles of macroeconomic fundamentals, but this time not as a substitute for microstructure analysis, but rather as a systematic means of incorporating lower frequency macroeconomic factors into higher frequency models.

A key technical limitation to combining macroeconomic and market data has been their different sampling frequencies (for example, daily prices versus quarterly GDP). Researchers attempting to combine macroeconomic and market data in the past have attempted to aggregate or interpolate the two datasets. Both methods may produce distorted versions of the original data, leading to biased results. The development of Mixed Data Sampling (MIDAS) regressions by Ghysels, Santa-Clara, and Valkanov (2004) provides a direct and efficient method to overcome this technical issue. The MIDAS methodology enables the inclusion of a low-frequency variable directly in a high-frequency regression through a small number of parameters that describe the relationship between the two variables. As a result, the issues associated with ad hoc aggregation are avoided.

The MIDAS methodology has been successfully employed to predict stock market volatility using macroeconomic indicators (Andreou, Ghysels, & Kourtellis, 2010) and to nowcast GDP using monthly financial data. However, the employment of MIDAS in the context of foreign exchange forecasting, specifically in relation to the problem of determining the optimal timing of FX executions, is still a relatively unexplored area of research. Our paper builds upon the MIDAS methodology as the first step in our pipeline to formally assess whether annual macroeconomic variables, commonly dismissed as too slow moving to be useful for predicting daily FX returns, have true predictive power for daily FX returns. In doing so, we will conduct a rigorous test of the macro relevance hypothesis at a frequency relevant for making decisions.

The global financial crisis of 2008 emphasized the significance of interconnectedness. A single asset view of risk was shown to be insufficient for explaining the nature of risk in the wake of the crisis, resulting in a transition to a network view of systemic risk. The Diebold and Yilmaz (2009, 2012, 2014) framework has been instrumental in advancing this transition. Using generalized forecast error variance decompositions from a Vector Autoregression (VAR) model, the authors enable the measurement of the size, direction, and dynamic evolution of spillovers between different elements of the financial system. This demonstrates the "connectedness" of various segments of the financial system, including stock markets, sovereign bond markets, and financial institutions.

Recent extensions of the Diebold-Yilmaz framework, such as Antonakakis, Chatziantoniou, and Gabauer (2020), have enabled the spillover network to be measured in a time-varying parameter (TVP-VAR) environment. This has allowed the spillover network itself to vary dynamically over time. While this literature has provided powerful descriptive insights into financial contagion and systemic risk (Garcia & Martinez, 2021), it has primarily been used in a diagnostic capacity. That is, it has primarily been used to determine periods of high risk or to identify systemically important institutions after the fact.

Our study departs from this existing body of literature in that we take a prescriptive approach. We do not stop at measuring spillovers; we operationalize the time-varying measures of connectedness in a predictive model, and as the basis for a "Low Connectedness" trading heuristic. By linking the descriptive

power of network analysis to the prescriptive goal of execution timing, we bridge a critical gap between the academic study of systemic risk and its practical application in asset management.

3. METHODOLOGY

The empirical methodology follows a multi-stage pipeline designed to investigate the research questions systematically. We begin with constructing daily log returns for each currency pair i as:

$$r_{i,t} = \ln(P_{i,t}) - \ln(P_{i,t-1}) \quad (1)$$

where $P_{i,t}$ represents the daily closing exchange rate on date t . This standardized preprocessing aligns seven foreign exchange series on a common calendar for unified analysis. From annual GDP growth and CPI inflation data, we derive macroeconomic features for each country c and year y :

$$m_{c,y}^{GDP} = \frac{GDP_{c,y} - GDP_{c,y-1}}{GDP_{c,y-1}}, \quad m_{c,y}^{CPI-diff} = CPI_{c,y} - CPI_{US,y} \quad (2)$$

These annual macroeconomic variables are carried forward to all trading days within year y , creating a novel step-function mapping of yearly macroeconomic data into daily timing models specifically designed for corporate foreign exchange payment optimization. We implement MIDAS regression to link low-frequency macroeconomic variables with daily exchange rate returns:

$$r_{i,t} = \alpha_i + \sum_{k=0}^K \beta_{i,k} B(\theta_i; k, K) m_{c,t-[k/D]}^{GDP} + \varepsilon_{i,t} \quad (3)$$

where $B(\theta; k, K)$ represents a Beta polynomial weight function with parameters θ_i , D rescales daily lags to annual frequency, and $\varepsilon_{i,t} \sim \mathcal{N}(0, \sigma_i^2)$. $r_{i,t}$, α_i , θ_i and $\beta_{i,k}$ denote respectively the return of asset, intercept, weight-shape parameter and the lag sensitivity. $m_{c,t-[k/D]}^{GDP}$ is the GDP based Macroeconomic variable, with c describing the country index and $t - [k/D]$ indicating the time alignment between high- and low-frequency data. This represents the first application of MIDAS methodology to African and G7 foreign exchange corridors explicitly designed for optimal payment timing. We employ the Bai-Perron multiple break framework to identify regime changes in each currency pair:

$$r_{i,t} = X'_{i,t} \beta_{i,j} + \varepsilon_{i,t}, \quad t \in [T_{j-1}, T_j] \quad (4)$$

where T_j represent estimated break dates that partition the sample into distinct regimes. This regime-wise re-estimation of timing models captures crisis-driven shifts including COVID-19 impacts and commodity price shocks. We model the vector of currency returns $r_t = [r_{1,t}, \dots, r_{N,t}]'$ using time-varying coefficients:

$$r_t = A_t r_{t-1} + u_t \quad (5a)$$

$$\text{vec}(A_t) = \text{vec}(A_{t-1}) + \eta_t \quad (5b)$$

where A_t represents an $N \times N$ coefficient matrix evolving as a random walk with innovation η_t , and $u_t \sim \mathcal{N}(0, \Sigma_t)$. This framework enables extraction of daily Diebold-Yilmaz connectedness measures from Bayesian TVP-VAR estimation specifically tailored for foreign exchange execution timing. From the TVP-VAR forecast error variance decompositions $\omega_{ij,t}$, we compute the Total Connectedness Index (ICI):

$$TCI_t = \frac{1}{N} \sum_{i \neq j} \omega_{ij,t} \times 100 \quad (6)$$

We construct dynamic adjacency matrices with weights:

$$[W_t]_{ij} = \omega_{ij,t} + \omega_{ji,t} \quad (7)$$

From these matrices, we compute network topology measures including degree centrality $d_i(t) = \sum_j [W_t]_{ij}$, network density $\frac{\sum_{i \neq j} [W_t]_{ij}}{N(N-1)}$, and clustering coefficients. This joint utilization of TVP-VAR spillovers to construct dynamic foreign exchange networks represents a novel approach to linking low-density or low-TCI days with optimal payment timing. We implement two benchmark models for one-day-ahead return forecasts. The autoregressive baseline model without macroeconomics variables is specified as follows:

$$\hat{r}_{i,t} = \theta_0 + \theta_1 r_{i,t-1} + e_{i,t} \quad (8)$$

where $r_{i,t-1}$ are the lagged returns. This comparison of advanced econometric (MIDAS, TVP-VAR) versus traditional autoregressive model provides novel insights for multi-currency corporate payment timing optimization. We define execution rules based on model outputs as follows. Rule A executes on the day with the highest predicted return, denoted as $\widehat{r}_{i,t}$. Rule B executes on the day with the lowest Total Connectedness Index TCI_t , while Rule C executes on the day with the lowest network density. The economic value of each rule ($P\&L$) is evaluated in terms of profit and loss per \$1 billion notional.

$$P\&L = \sum_t (P_{i,t+1} - P_{i,t}) \times I_t \quad (9)$$

The pairwise connectedness measures derived from the Time-Varying Parameter Vector Autoregression (TVP-VAR) model are used to construct the weighted adjacency matrix of the foreign exchange (FX) network. Building on this structure, we implement a backtesting framework to evaluate the performance of four distinct execution timing strategies. The momentum strategy executes trades following recent positive performance, while the low volatility strategy targets periods characterized by reduced market fluctuations. The low connectedness strategy initiates trades when the FX network exhibits weaker systemic linkages, indicating lower contagion risk. Finally, a random execution strategy serves as a benchmark, executing trades at arbitrary intervals. Strategy performance is assessed using standard evaluation metrics, including the Sharpe ratio, cumulative return, and maximum drawdown.

Empirical analysis

Our dataset integrates high-frequency (daily) financial data with low-frequency (annual) macroeconomic indicators over a comprehensive sample period, enabling a robust analysis of FX dynamics across a diverse set of economies. The high-frequency component comprises daily closing prices for seven exchange rates relative to the U.S. Dollar: the Canadian Dollar (CAD/USD), Chinese Yuan (CNY/USD), Congolese Franc (CDF/USD), Euro (EUR/USD), Japanese Yen (JPY/USD), South African Rand (ZAR/USD), and Nigerian Naira (NGN/USD). Sample periods vary by currency, with developed market pairs - EUR/USD, JPY/USD, and CAD/USD extending from 2000 to 2024, offering over 6,000 daily observations, while emerging market currencies - CNY/USD, CDF/USD, ZAR/USD, and NGN/USD

provide slightly shorter spans beginning in 2005 due to data availability. The low-frequency macroeconomic component includes annual real GDP growth rates and CPI inflation figures from 1990 to 2023 for each corresponding country.

This selection captures a broad spectrum of global economic activity, encompassing major developed economies (U.S., Eurozone, Japan, Canada), a leading emerging Asian power (China), and three key African economies: South Africa, Nigeria, and the Democratic Republic of Congo. The developed market currencies serve as liquidity benchmarks and global risk indicators, aligning with the carry trade dynamics documented by Menkhoff et al. (2012), while CNY/USD reflects China's centrality in global trade networks, as emphasized by Cheung et al. (2019). African currencies are strategically included due to the continent's growing role in global value chains: D.R. Congo for its mineral wealth, South Africa as a financial hub, and Nigeria as the region's largest economy. This geographic and economic diversity enables us to explore how macroeconomic information and volatility regimes transmit from developed to emerging markets, consistent with Rey's (2013) core-periphery framework, and to examine the propagation of regional shocks across global FX networks, contributing to the literature on spillover and connectedness dynamics as advanced by Diebold and Yilmaz (2014).

The first step in our analysis is to determine whether low-frequency macroeconomic data can enhance high-frequency return forecasts. We use MIDAS regressions to formally test this. Table 1 presents a direct comparison of in-sample (full dataset) fit between a baseline Autoregressive (AR(1)) model and our proposed MIDAS model, which incorporates annual macroeconomic fundamentals. The AR(1) serves as a benchmark representing the view that returns are only predictable by their immediate past, while the MIDAS model tests the incremental value of economic data. The results are unambiguous.

Table 1

MIDAS vs. AR(1) Comparison

Pair	AR1_R ²	MIDAS_R ²	R ² _Improvement	AIC	Theta_0	Theta_1
CADUSD	0.00041	0.00068	0.00028	-39406.34	1.00000	1.00000
CNYUSD	0.00008	0.00164	0.00155	-48898.38	1.00000	1.00000
CDFUSD	0.06445	0.06611	0.00167	-19272.31	1.00000	1.00000
EURUSD	0.00000	0.00003	0.00003	-39165.13	1.00000	1.00000
JPYUSD	0.00076	0.00082	0.00005	-38090.84	1.00000	1.00000
ZARUSD	0.00043	0.00048	0.00005	-41096.87	1.00000	1.00000
NGNUSD	0.02941	0.02971	0.00030	-38694.56	1.00000	1.00000

Source: authors' own computation - Theta_0 and Theta_1 are coefficients in equation (8)

The *MIDAS_R²* is higher than the *AR1_R²* for every currency pair, and the *R²_Improvement* column, which is positive across the board, quantifies this enhancement. This provides compelling evidence that adding annual GDP growth and inflation data consistently improves the model's ability to explain daily FX returns.

This result has important economic implications, directly challenging the traditional "disconnect puzzle" by showing that foreign exchange markets do, in fact, reflect broader economic conditions even at the daily frequency. For practitioners such as corporate treasurers or fund managers, this suggests that macroeconomic perspectives, including trends in output or inflation, provide valuable insights for short-term trading decisions. Ignoring these fundamentals, even over brief horizons, leads to suboptimal performance both statistically and economically.

We next investigate whether FX markets operate in distinct regimes. We employ structural break tests to endogenously identify points of significant change in the volatility process of each currency pair. Figure

1 plots the price series for each currency, with vertical red lines indicating the dates of detected structural breaks. The analysis identified 14 distinct breaks across the sample, which often coincide with periods of known global economic turmoil, such as the 2008 Global Financial Crisis and the onset of the COVID-19 pandemic in 2020. To understand the economic significance of these regimes, we analyze the market's behavior within them.

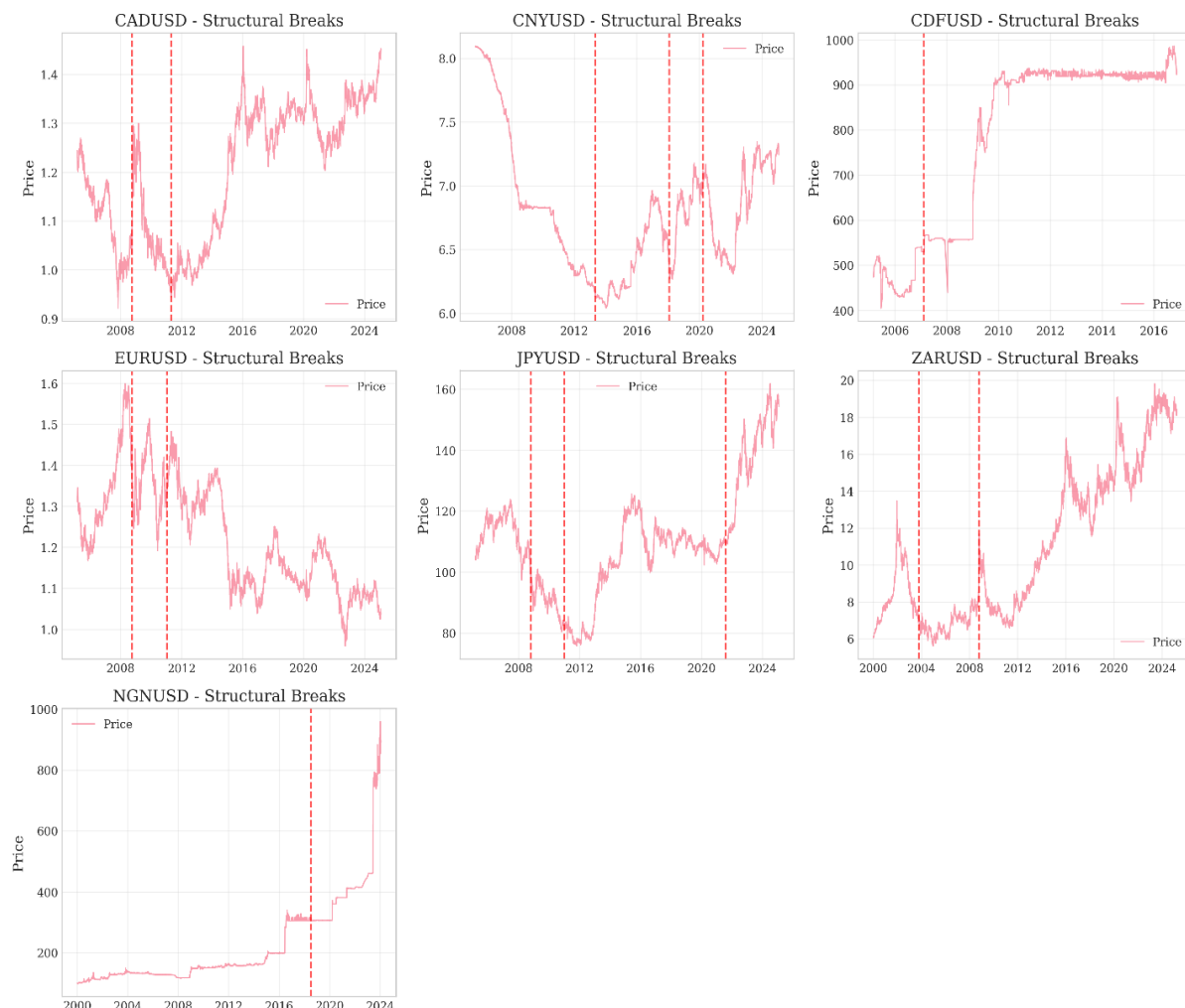


Figure 1. Detected structural breaks in FX volatility

Figure 2 below provides a multi-faceted view of the identified regimes, revealing that volatility in high-state regimes is, on average, 1.67 times higher than in low-state regimes a clear indication that the detected breaks correspond to economically meaningful shifts in market dynamics. The top-left panel, a boxplot of volatility distribution by currency pair, highlights significant heterogeneity in volatility levels across currencies. The top-right panel illustrates the persistence of these regimes, many of which last for hundreds of days, while the bottom-left panel maps the risk-return profile for each currency within each regime, showing stark differences in trade-offs between risk and return. The bottom-right panel offers a timeline that visually captures the duration and volatility intensity of each regime. Together, these insights confirm that risk is not static, a finding with crucial implications for both theory and practice. Models assuming constant parameters such as static volatility or correlation are fundamentally misspecified and prone to failure during periods of market stress.

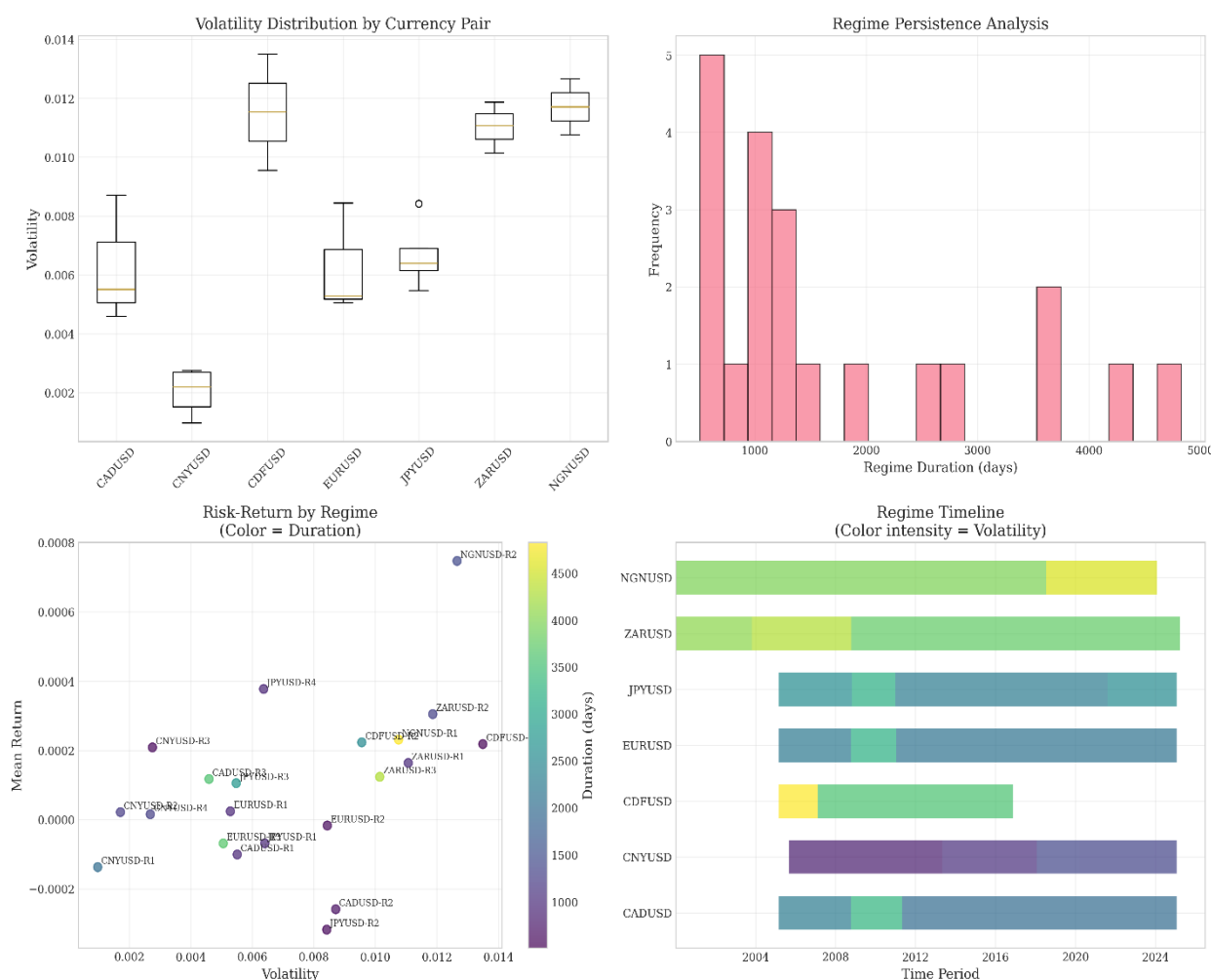


Figure 2. Regime volatility analysis

This state-dependence means that the cost of execution error rises sharply in volatile regimes, underscoring the need for adaptive, regime-aware execution strategies. Firms can improve performance by adjusting their trading policies dynamically, for example by demanding wider spreads or deploying more sophisticated algorithms during high-volatility periods.

Having established that markets are not static, we now turn to quantifying their interconnectedness using a TVP-VAR model. Figure 3 presents our analysis of the Total Connectedness Index (TCI). The TCI measures the contribution of spillovers from other currencies to the total forecast error variance of the system. A higher value indicates greater interdependence. Our findings show that the index is highly dynamic, with clear surges during periods of market stress. This indicates that the vast majority of forecast error variance in the system, on average, comes from spillovers between currencies rather than from idiosyncratic shocks. The top panel illustrates the evolution of the TCI over time, with pronounced surges during periods of market stress, marked by vertical red lines.

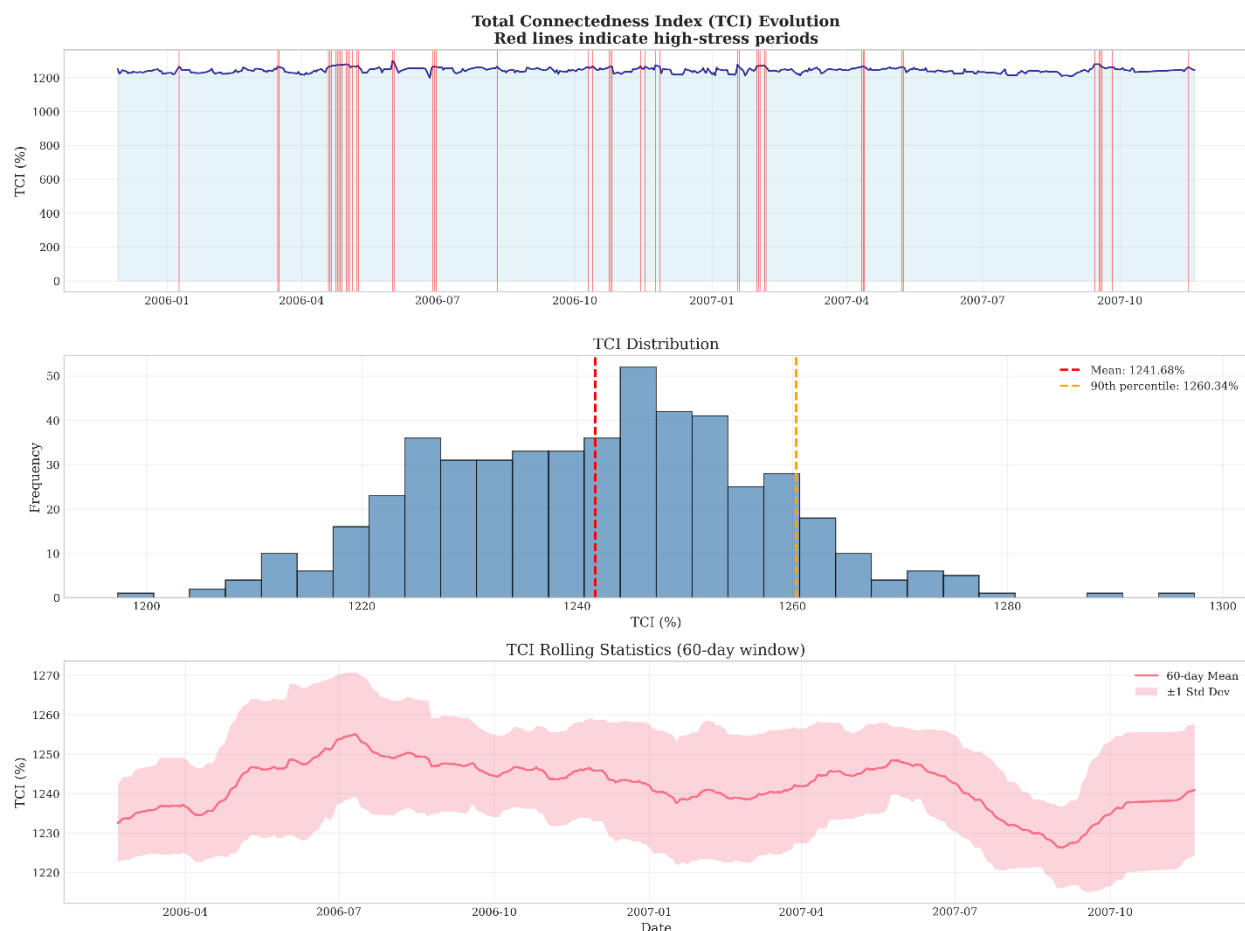


Figure 3. TCI evolution analysis

These spikes represent quantitative evidence of financial contagion, where the transmission of shocks intensifies, dramatically reducing the effectiveness of diversification. The middle panel displays the distribution of the TCI, confirming its elevated average level, while the bottom panel smooths the series using a 60-day rolling mean and standard deviation to highlight the cyclical nature of connectedness. This analysis has direct economic implications: when the TCI rises, a shock to one currency is far more likely to propagate throughout the system, heightening systemic risk. For global portfolio managers, elevated TCI levels serve as a critical warning signal to reduce exposure or pivot toward assets that are demonstrably less connected to the core FX network. Moreover, the pairwise spillover measures that make up the TCI allow for the construction and analysis of evolving FX network structures.

Figure 4 offers a comprehensive visualization of the FX spillover network, revealing a “small-world” architecture sparse yet highly clustered which is characteristic of systems where information and shocks can propagate rapidly. The top-left panel presents the network graph, where currencies are represented as nodes and spillovers as directed edges. Node size reflects degree centrality, indicating total influence, while node color represents betweenness centrality, capturing each currency's role as a bridge within the system. The heatmap on the right displays the connectedness matrix, detailing the intensity of spillovers from each currency (rows) to all others (columns). At the bottom, bar charts quantify the centrality measures, identifying EURUSD and NGNUSD as currencies with notably high degree centrality.

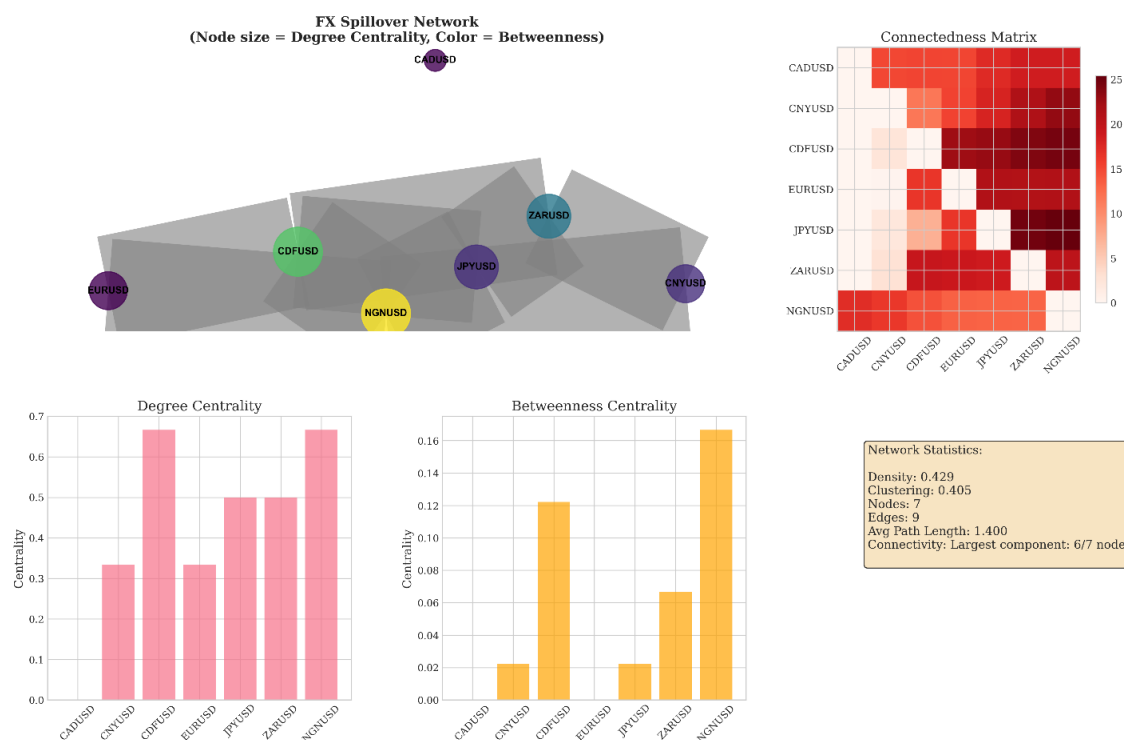


Figure 4. Enhanced spillover network

This suggests their outsized influence in transmitting shocks across the FX network. Network statistics further confirm this structure, with a density of 0.43 and an average clustering coefficient of 0.41, hallmarks of systems where local clusters can amplify and spread volatility quickly. Economically, EURUSD and NGNUSD emerge as “systemically important currencies,” acting as primary conduits for market-wide turbulence. For firms managing multi-currency exposures, this underscores the need to closely monitor these central nodes, as shocks originating from them are more likely to trigger widespread market responses.

The final and most critical part of our analysis is to determine whether these complex market insights can be translated into superior execution strategies. We backtest five strategies: Momentum, Low Volatility, Low Connectedness, and Random. Table 2 in Appendix reports the aggregate performance metrics for each strategy across all currency pairs. The results are both surprising and decisive. The Momentum strategy stands out as the clear winner, delivering a robust average annual Sharpe ratio of 2.37 and an average annual return of 7.0%. Additionally, CAD/USD and EUR/USD have the second-best strategy that is low connectedness. CDF/USD, and JPY/USD have the second-best low-volatility. ZAR/USD and NGN/USD have the second-best strategy that is random. In stark contrast, the other heuristic strategies, Low Volatility and Low Connectedness, failed to generate positive risk-adjusted returns.

Figure 5 provides a multi-faceted evaluation of the risk and return profiles of the tested execution heuristics. The results across all panels point to the unambiguous superiority of the Momentum strategy. The Risk-Return Profile (top-left panel) plots each strategy's outcome in terms of annualized return versus annualized volatility. The Momentum strategy is the only one that occupies the desirable top-left quadrant, indicating that it generates high positive returns with moderate volatility. In contrast, the Low Volatility, Low Connectedness, and Random strategies are all clustered in the inefficient bottom-right space, yielding near-zero or negative returns for similar or higher levels of risk.

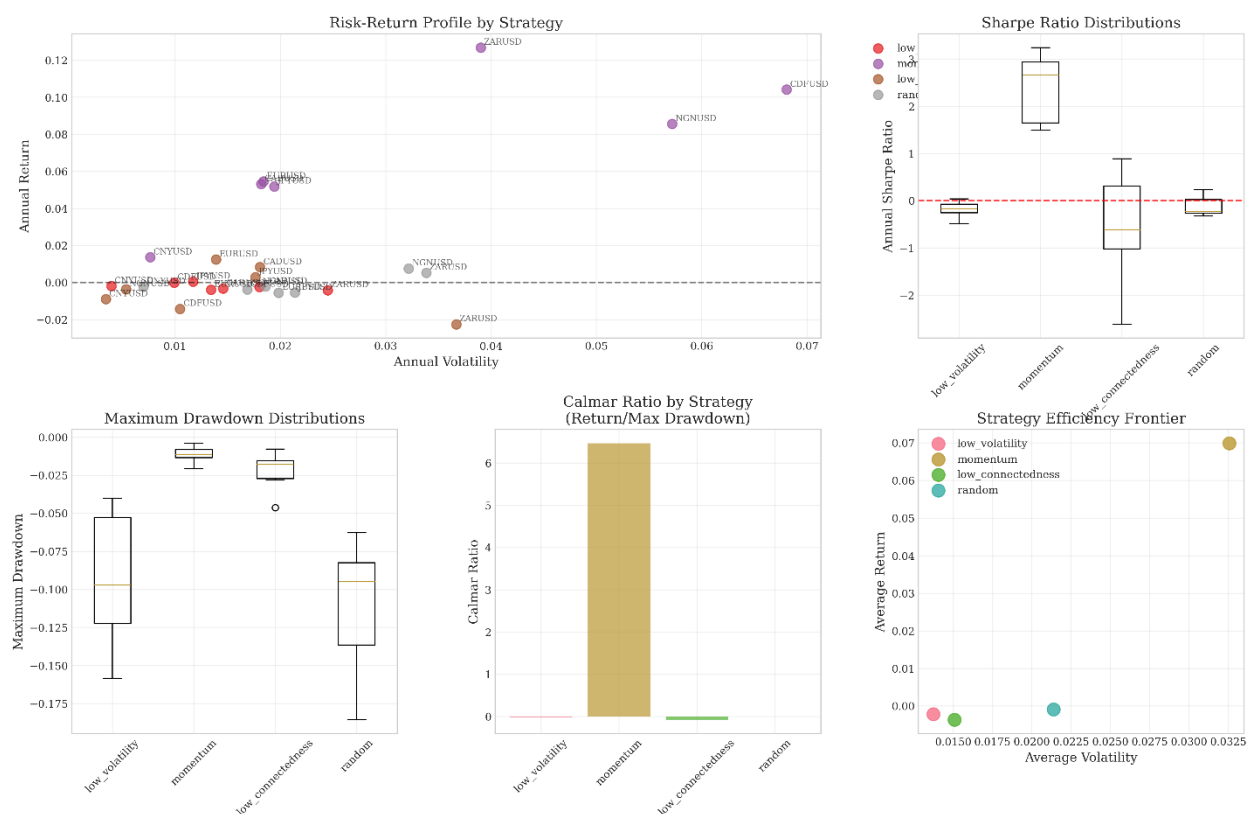


Figure 5. Comprehensive risk-return analysis

This finding is reinforced by the Sharpe Ratio Distributions (top-right panel). The boxplot for the Momentum strategy is located entirely in positive territory, with a median Sharpe ratio well above 2.0, and is followed by the low-connectedness strategy which has the second highest Sharpe ratio. This not only signifies strong risk-adjusted returns but also remarkable consistency. The other heuristics, however, have distributions centered near or below zero, indicating they fail to generate returns that compensate for the risk taken. From a risk management perspective, the Maximum Drawdown and Calmar Ratio panels are particularly telling. The Momentum strategy exhibits a very small maximum drawdown, highlighting its strong capital preservation characteristics - a feature of critical economic importance for any institutional investor. This translates into an exceptionally high Calmar Ratio (Return/Max Drawdown), which dramatically exceeds that of any other strategy. Finally, the Strategy Efficiency Frontier (bottom-right panel) synthesizes these results, showing that the Momentum strategy alone defines the efficient frontier. All other heuristics lie deep inside this frontier, confirming they are suboptimal choices, as they offer lower returns for any given level of risk.

Figure 6 provides a clear visualization of the superior performance consistency of the Momentum strategy, as evidenced by the boxplots of Sharpe ratios and annual returns. The Momentum strategy stands out with a distribution of Sharpe ratios that is almost entirely positive and centered well above those of competing strategies, which tend to cluster near or below zero. This elevated and tight distribution underscores a crucial economic insight: the effectiveness of the Momentum strategy is not driven by a few isolated periods of strong performance but rather by a persistent and reliable pattern. Such predictability is highly valuable for institutional investors, as it leads to more stable and forecastable outcomes.

In contrast, the broader and often negative distributions of other strategies indicate inconsistent and potentially value-destroying performance. For risk-sensitive entities like corporate treasurers or asset

managers, the stability and reliability offered by the Momentum approach provide a compelling case for its adoption in execution strategies.

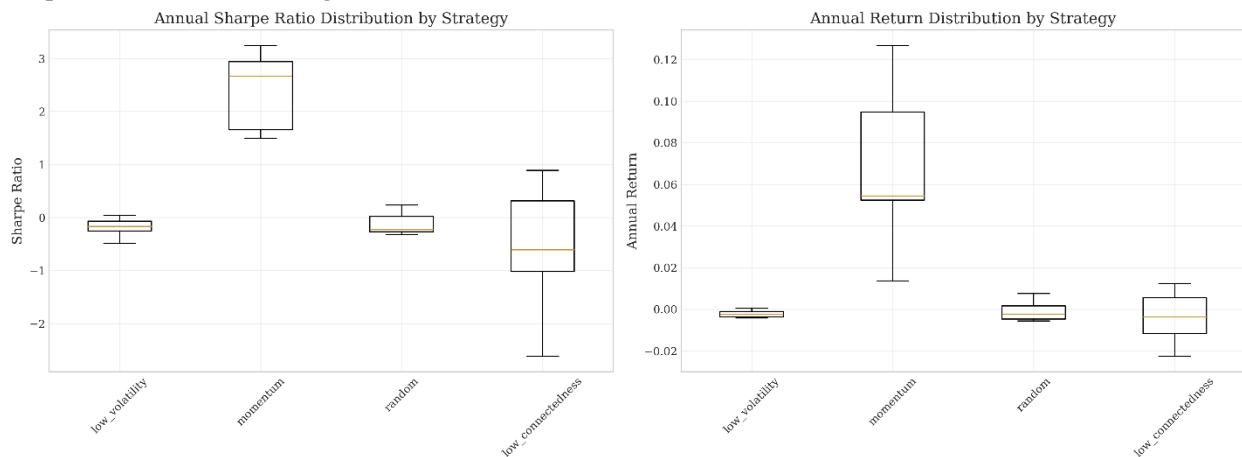


Figure 6. Backtest performance

Figure 7 provides a comprehensive attribution analysis that reinforces the dominance of the Momentum strategy across multiple performance dimensions. The heatmap in the top-left panel reveals that Momentum's outperformance indicated by warm colors is broad-based across most currency pairs, confirming that its success is not limited to a specific asset but reflects a generalizable pattern. The performance ranking bar chart in the top-right panel further highlights that Momentum is the only strategy with a statistically and economically significant positive mean Sharpe ratio. Most compellingly, the win rate plot in the bottom-right shows that Momentum achieves a win rate exceeding 75%, meaning that for every four execution decisions, three are expected to be profitable on a risk-adjusted basis.

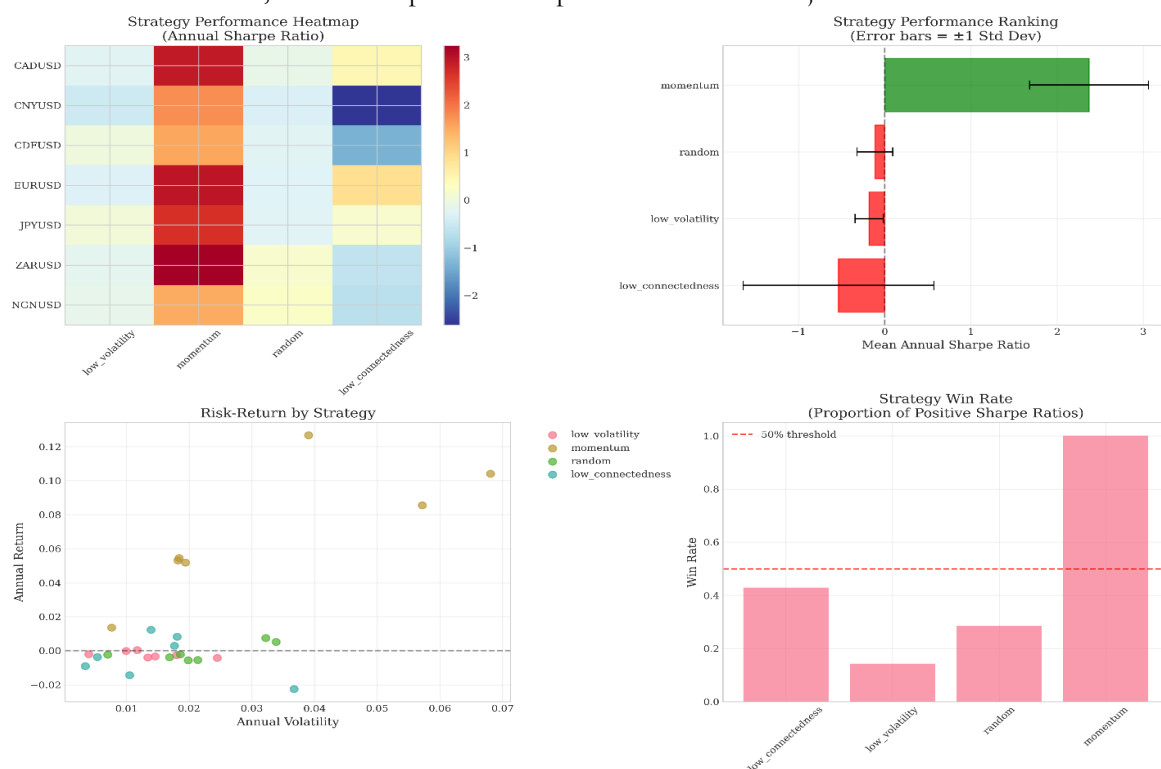


Figure 7. Strategy performance attribution

This high and consistent success rate underscores the economic viability of the strategy, making it highly attractive for practical implementation by institutions seeking stable performance and minimal exposure to extended periods of underperformance. Collectively, these findings provide strong evidence that a simple, robust heuristic like Momentum can outperform more complex approaches, delivering both predictability and superior returns

5. CONCLUSION

This study embarked on an ambitious agenda to build an integrated framework for analyzing foreign exchange markets, bridging the gap between low-frequency macroeconomic theory and high-frequency market practice. We sought to answer four central questions concerning the role of macro-fundamentals, the existence of market regimes, the dynamics of spillovers, and the practical application of these insights through common execution heuristics.

Our findings provide clear answers to each question. We demonstrate that slow-moving, annual macroeconomic variables contain significant predictive power for daily FX returns, improving model fit over a standard autoregressive baseline and challenging the conventional wisdom of a market "disconnect." We confirm that FX markets are not static but evolve through distinct structural regimes, with volatility being 1.67 times higher in crisis periods. Furthermore, using a time-varying network model, we quantify the intense and dynamic nature of spillovers, showing that market interconnectedness is a critical and fluctuating source of systemic risk. Finally, and most strikingly, our backtesting analysis reveals that a simple, robust momentum heuristic, with an average annual Sharpe ratio of 2.37, decisively outperforms other common, economically-motivated execution rules such as those based on low volatility or low market connectedness.

The economic implications of these findings are profound. The research highlights that while complex econometric models are invaluable for understanding market structure and risk, simple and robust heuristics can be superior for practical implementation. The failure of the "Low Volatility" and "Low Connectedness" strategies suggests that simply avoiding risk is not, in itself, a profitable timing strategy; instead, systematically following recent trends via a momentum rule proves to be a more effective approach to capturing positive returns.

Based on these findings, we offer a key recommendation for corporate treasurers, portfolio managers, and other market participants: employ a dual approach. Use sophisticated econometric and network models for strategic risk assessment and to understand the prevailing market environment. However, for the tactical decision of execution timing, prioritize simple, robust, and well-tested heuristics like momentum. The goal should not be to build a perfect forecasting model, which may be an illusory quest, but to implement a consistently effective decision rule.

This research opens several avenues for future work. The framework could be extended to other asset classes, such as commodities or cryptocurrencies, to test the universality of these findings. Investigating the underlying behavioral or risk-based drivers of the powerful momentum premium in FX markets remains a fertile area for research. Finally, exploring combinations or conditional applications of these heuristics, perhaps using the regime-switching model to toggle between strategies, could potentially yield even more effective execution frameworks.

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APPENDIX A1: TABLE 2 - BACKTEST RESULTS

Pair	Strategy	mean_return	std_return	sharpe_ratio	annual_sharpe	cumulative_return	annual_return	annual_volatility	max_drawdown
CADUSD	low_volatility	-0.00027	0.00421	-0.06426	-0.22229	-0.06665	-0.00324	0.01457	-0.09728
CADUSD	momentum	0.00432	0.00525	0.82251	2.91793	1.87754	0.05308	0.01819	-0.00919
CADUSD	low_connect edness	0.00069	0.00522	0.13205	0.45917	0.01634	0.00830	0.01808	-0.02614
CADUSD	random	-0.00017	0.00537	-0.03240	-0.11213	-0.04562	-0.00208	0.01859	-0.09469
CNYUSD	low_volatility	-0.00016	0.00115	-0.14086	-0.48751	-0.03831	-0.00194	0.00397	-0.05035
CNYUSD	momentum	0.00113	0.00221	0.50988	1.77727	0.30954	0.01360	0.00765	-0.00395
CNYUSD	low_connect edness	-0.00075	0.00099	-0.75882	-2.61775	-0.01795	-0.00901	0.00344	-0.01775
CNYUSD	random	-0.00019	0.00202	-0.09347	-0.32344	-0.04524	-0.00227	0.00701	-0.06271
CDFUSD	low_volatility	0.00000	0.00287	-0.00141	-0.00490	-0.00117	-0.00005	0.00993	-0.04019
CDFUSD	momentum	0.00828	0.01965	0.42152	1.52856	1.78692	0.10405	0.06807	-0.00721
CDFUSD	low_connect edness	-0.00120	0.00303	-0.39522	-1.36010	-0.02844	-0.01427	0.01049	-0.02824
CDFUSD	random	-0.00032	0.00487	-0.06533	-0.22593	-0.04643	-0.00381	0.01687	-0.09489
EURUSD	low_volatility	-0.00032	0.00387	-0.08320	-0.28772	-0.07823	-0.00386	0.01342	-0.13844
EURUSD	momentum	0.00443	0.00532	0.83419	2.96125	1.95920	0.05453	0.01841	-0.01362
EURUSD	low_connect edness	0.00103	0.00401	0.25564	0.89058	0.02471	0.01238	0.01390	-0.01328
EURUSD	random	-0.00046	0.00573	-0.08040	-0.27780	-0.11162	-0.00551	0.01985	-0.18574
JPYUSD	low_volatility	0.00004	0.00339	0.01136	0.03936	0.00812	0.00046	0.01173	-0.05517
JPYUSD	momentum	0.00422	0.00561	0.75247	2.66800	1.81869	0.05183	0.01943	-0.01324
JPYUSD	low_connect edness	0.00025	0.00509	0.04817	0.16710	0.00559	0.00295	0.01764	-0.01796
JPYUSD	random	-0.00046	0.00618	-0.07370	-0.25465	-0.11102	-0.00545	0.02140	-0.16005
ZARUSD	low_volatility	-0.00035	0.00707	-0.04940	-0.17081	-0.11059	-0.00418	0.02450	-0.15850
ZARUSD	momentum	0.00999	0.01127	0.88660	3.24577	20.80057	0.12668	0.03903	-0.02075
ZARUSD	low_connect edness	-0.00189	0.01060	-0.17878	-0.61290	-0.04579	-0.02250	0.03671	-0.04639
ZARUSD	random	0.00044	0.00977	0.04485	0.15572	0.13050	0.00527	0.03386	-0.11326
NGNUSD	low_volatility	-0.00021	0.00520	-0.03943	-0.13643	-0.06308	-0.00246	0.01801	-0.10651
NGNUSD	momentum	0.00686	0.01651	0.41543	1.49466	6.00089	0.08550	0.05720	-0.01123
NGNUSD	low_connect edness	-0.00030	0.00155	-0.19604	-0.67799	-0.00728	-0.00363	0.00536	-0.00780
NGNUSD	random	0.00063	0.00929	0.06730	0.23394	0.19022	0.00753	0.03220	-0.07018