Swap Market Volatility and Future Macroeconomic Risk: An Analysis of Predictive Content

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Abstract

This study examines the relationship between swap market volatility and macroeconomic uncertainty across USD, EUR, and JPY markets, exploring the predictive content that swap volatility may hold for future macro risk. Macroeconomic uncertainty is proxied using market-based, news-based, and model-based measures, while swap volatility is captured through three approaches: GARCH-based conditional volatility of swap rate changes, its low-frequency component extracted via spline fitting and swaption-implied volatility.

Results reveal strong associations between swap volatility and macroeconomic risk, with these links intensifying in recent years. Granger causality tests confirm storng reverse causality and two-way feedback dynamics, with macro shocks often driving swap volatility.

Forecasting evaluations highlights the limits of prediction: swap volatilities improve model fit in-sample, while out-of-sample gains are modest given the persistence of macro uncertainty. Still, even small improvements matter, showing that swap volatility is not noise but a valuable reflection of market expectations about future conditions.

The broader contribution is clear: swap-based volatilities are not stable and consistent forecasters, but they are highly effective mirrors of uncertainty. Their continuous feedback with the macroeconomy makes them essential to consider in policymaking, trading, and research.

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Resumo

A dissertação analisa a relação entre a volatilidade do mercado de swaps e a incerteza macroeconómica nos mercados USD, EUR e JPY, explorando a capacidade preditiva que a volatilidade dos *swaps* pode conter relativamente ao risco macroeconómico futuro. A incerteza macroeconómica é representada através de medidas baseadas no mercado, em notícias e em modelos, enquanto a volatilidade dos *swaps* é captada por três abordagens: a volatilidade condicional baseada em modelos GARCH, o seu componente de baixa frequência extraído por ajuste de *splines* e a volatilidade implícita de *swaptions*.

Os resultados revelam uma relação forte entre a volatilidade dos *swaps* e o risco macroeconómico e que se intensificou nos últimos anos. Testes de causalidade de Granger confirmam uma forte causalidade inversa e dinâmicas de *feedback* bidirecionais, sendo os choques macroeconómicos frequentemente os motores da volatilidade dos *swaps*.

As avaliações de previsão evidenciam os limites da capacidade preditiva: a volatilidade dos *swaps* melhora o ajustamento dos modelos dentro da amostra, enquanto os ganhos fora da amostra são modestos, dada a persistência da incerteza macroeconómica. Ainda assim, mesmo pequenas melhorias são relevantes, demonstrando que a volatilidade dos *swaps* não é mero ruído, mas sim um reflexo valioso das expectativas do mercado sobre as condições futuras.

A contribuição mais ampla é clara: as volatilidades baseadas em *swaps* não constituem previsores estáveis e consistentes, mas funcionam como espelhos altamente eficazes da incerteza. A sua interação contínua com a macroeconomia torna-as essenciais a considerar em matéria de definição de políticas, negociação e investigação académica.

Título: "Volatilidade no Mercado de Swaps e Risco Macroeconómico Futuro: Uma Análise da Capacidade Preditiva"

Autor: Antonio Filonzi

Palavras-chave: Macroeconomia, Poder Preditivo, Swaps, Incerteza, Volatilidade

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1. Introduction

Volatility in interest rate derivatives markets has surged to multi-year highs in recent times, reflecting a profound shift in the macroeconomic and geopolitical environment. Since late 2021, both realized volatility in interest rate swaps and implied volatility from swaptions have climbed sharply, driven by repeated inflation surprises, unprecedented monetary tightening cycles, persistent policy uncertainty and rising geopolitical risks. While some normalization has occurred since early 2023, these measures remain well above their historical average, signaling that uncertainty around future interest rate paths and macroeconomic outcomes is still elevated (Altig et al. 2020; Cascaldi-Garcia et al. 2023; Sarisoy, 2023; 2024). This changing environment sparks research interest in exploring the relationship between rates volatility and macroeconomic uncertainty, and in investigating whether new dynamics have recently emerged.

A strong correlation between swaps and macroeconomic volatility has long been recognized, with studies documenting both comovement and reverse causality (Azad et al., 2011; 2012). More recent work (Sarisoy, 2023; 2024) rethinks interest rates volatility as a possible forward-looking signal of macroeconomic fragility, raising a natural question: to what extent do rates volatility, specifically from swap and swaption markets, not just react to, or co-move with, macroeconomic risk, but actually anticipate it? If market participants progressively internalize more accurate information about future macroeconomic shocks, refining their expectations, then today's rate volatility may incorporate forward-looking signals about tomorrow's uncertainty. Understanding the nature of this association is crucial for policymakers, investors, and researchers, as it brings light on how information flows between financial markets and the real economy over time.

This thesis address that question by focusing on swap rates rather than bond yields, considered the former a cleaner measure of market expectations about future macroeconomic conditions and following the seminal work of Azad et al. (2011; 2012).

The analysis covers USD, EUR, and JPY markets, spanning the broadest available datasets (1985–2025). Three measure of swap market volatility are studied: conditional GARCH volatiltiy of swap rates, its slow-moving low-frequency extracted via spline curve fitting, and implied volatility from swaptions. To approximate macroeconomic uncertainty, the study considers model-based measures (GARCH volatilities of major economic indicators and exchange rates), news-based indices (e.g. EPU, MPU, TPU), and market-based benchmarks (VIX, MOVE).

Swap rates, swaptions, foreign exchange and macroeconomic data are modeled through their volatilities to obtain robust measures of both swap rates volatility – the independent variable – and macroeconomic uncertainty – the dependent variable. Correlation analysis and Granger causality tests are then employed to map the strength and direction of the relationship, identifying lead–lag dynamics and clarifying whether swaps contain signals beyond simple co-movement. Building on these findings, predictive regressions evaluate whether swap volatility improves forecasts of macro uncertainty beyond an autoregressive (AR(1)) benchmark, following Ludvigson, Ma, and Ng (2021), who emphasize the persistence of macroeconomic uncertainty and its endogenous amplification of shocks. This allows testing the genuine forecasting power of rate derivatives data once that persistence is controlled for.

The findings reveal that swap volatility is not a breakthrough in forecasting macroeconomic risk, but is far from irrelevant. In-sample, swap-based volatilities carry genuine explanatory content, delivering positive increments of R^2 relative to the autoregressive benchmark in nearly all cases. The low-frequency component of swap rate volatility captures broad and persistent macro risk, while swaption-implied volatility provides sharper but episodic signals – a contrast consistent with Berger, Dew-Becker, and Giglio (2020), who show that realized volatility shocks, rather than forward-looking uncertainty innovations, drive macroeconomic outcomes.

Out-of-sample, predictive power becomes more selective once measured against the demanding AR(1) benchmark. Nevertheless, improvements of 1–2% in forecast accuracy survive across different cases, and in the context of highly persistent macroeconomic volatility, even small improvements represent a genuine edge over pure autoregressive memory. Furthermore, swap volatilities consistently lead movements in option-implied bond volatility, supporting the central premise of this research which sees swap-based measures providing a cleaner and more immediate signal of monetary policy risk than government bond yields, which are influenced by debt issuance, credit risk perception, and fiscal dynamics.

The analysis also reveals robust correlations of swap-based volatilities with policy uncertainty indices, inflation and core inflation volatility, FX volatility, and option-implied benchmark measures, while confirming strong swaps-macro reverse causality, and feedback dynamics.

Overall, the results contribute to a deeper understanding of the complex two-way relationship between swap market volatility and macroeconomic uncertainty. By clarifying both the limits of predictive power and the strength of contemporaneous links, the study offers new evidence on how rate derivatives markets process and reflect macroeconomic risk over time, across different regimes.

2. Literature Review

The relationship between interest rate derivatives markets and macroeconomic uncertainty has traditionally been studied from the perspective of macro-to-financial markets transmission, treating swap rate volatility as dependent variable shaped by macroeconomic risk. Early studies by Azad, Fang, and coauthors (2011; 2012) exemplify this approach, decomposing swap market volatility into high- and low-frequency components using the Asymmetric Spline-GARCH (ASP-GARCH) methodology of Engle and Rangel (2012). Their analyses of US, UK and Japanese swap markets show that the slow-moving component closely co-moves with macroeconomic uncertainty, with Granger tests confirming both spillovers and feedback. While these studies acknowledge bidirectionality, their framing remains explanatory rather than predictive. The question of whether swap volatility itself contains forward-looking information about macro risk remained largely unexplored.

Uncertainty more broadly has been conceptualized in different ways across macro and finance. Bloom (2009) demonstrates that uncertainty shocks, proxied by stock market volatility spikes, trigger contractions in output and investment, in the short-term. Related work in asset pricing decomposes option-implied variance into expected volatility and variance risk premia (Bollerslev, Tauchen, and Zhou 2009; Bekaert and Hoerova 2014) as well as in high- vs. low-frequency risk (Egloff, Leippold, and Wu 2010) showing strong predictive power for economic activity. In line with this stream of research, Giglio, Kelly, and Pruitt (2016) show that systemic risk measures derived from option markets forecast recessions, while Adrian, Boyarchenko, and Giannone (2019) highlight how equity market volatility signals "vulnerable growth" by raising downside risks to output. Berger, Dew-Becker, and Giglio (2020) argue instead that stock market realized volatility shocks, not forward-looking uncertainty, drive macro outcomes. Of particular relevance here, Ludvigson, Ma, and Ng (2021) demonstrate that while surges in macroeconomic uncertainty are often an endogenous response to recessions, they nonetheless play a critical role in amplifying downturns once triggered by other shocks. Together these studies place stock market volatility as both a reflection and a driver of macroeconomic fragility.

Interest rate derivatives have progressively drawn attention. Hattori (2017) documents that swaption-implied volatility predicts realized swap rate volatility in USD and EUR, finding weaker results for JPY market, while Liu and Xie (2023) show that US model-free implied volatilities outperform realized and GARCH estimates across horizons in predicting future swap rate volatility, especially during periods of policy stress. Drechsler, Savov, and Schnabl (2018) connect monetary policy to volatility and risk premia, while Tillmann (2020) demonstrates how elevated policy uncertainty compresses term premia and weakens yield curve responses to central bank actions. Wright (2011) similarly finds that inflation uncertainty raises term premia across international bond markets, highlighting the link between macro risk and fixed income pricing.

Parallel research developed news- and text-based measures of uncertainty. The Economic Policy Uncertainty (EPU) index of Baker, Bloom, and Davis (2016) has become a standard benchmark, with extensions to monetary policy uncertainty (Husted, Rogers, and Sun 2016) and trade policy uncertainty (Baker et al. 2020) enriching the set of proxies available to capture macroeconomic uncertainty.

Altig et al. (2020) compare financial, survey, and news-based measures, showing that uncertainty is multidimensional and spiked consistently across measures during COVID. Baker, Bloom, Davis, and Terry (2020) strenghten this conclusion, documenting unprecedented uncertainty surges in pandemic times, across markets, forecasts, and firm surveys. Cascaldi-Garcia et al. (2023) review this literature, emphasizing how uncertainty is not a solid and concrete object but a multifaceted phenomenon, with financial markets, economic releases surveys, and news sources each capturing distinct but complementary dimensions that jointly shape macroeconomic risk.

The most recent contributions, here particularly relevant, directly links option-implied interest rate volatility to future macroeconomic outlook. Sarisoy (2023) shows that spikes in implied volatility are associated with greater downside risks to GDP and inflation persistence, reframing interest rate volatility not as a passive response to macro uncertainty, but as a forward-looking signal of macroeconomic fragility**.** Sarisoy (2024) decomposes implied volatilites into macro drivers (survey-based measures of growth and inflation uncertainty), stressing the role of lower inflation uncertainty in explaining their decline, after spring 2023.

Sarisoy’s work widens the debate on the direction of causality, questioning whether rates volatility signals future macroeconomic conditions, or vice versa. At the same time, it remains confined to the USD market, relies on bond yields rather than swap rates, focuses on the distribution of macroeconomic outcomes rather than on uncertainty itself and does not directly test real predictive power of neither variable.

3. Data

All data employed in this study are collected up to July 25, 2025, a cut-off date that captures the recent increase in macroeconomic uncertainty sparked by inflation shocks, trade and geopolitical tensions. The samples include nearly the full history available for each variable, with series lengths varying according to data availability. Detailed coverage for each series is reported in Table 1 (Appendix).

3.1. Swap Market Volatility

A swap rate is the fixed interest rate (fixed leg) in an interest rate swap (IRS) contract that equates the present value of fixed and floating cash flows, with the floating leg tied to a benchmark rate. Since multiple contract structures and benchmarks exist, there is no single universal quotation for swap rates. For this study, daily IRS series for USD, EUR and JPY were taken from Datastream, as they provide the longest consistent historical coverage. To validate the data, alternative swap curves from Bloomberg were also collected. These series, which are priced against overnight benchmarks and have shorter coverage, were compared with the Datastream series. As shown in Figure 1 (Appendix), their evolution is virtually identical. The analysis therefore proceeds using the Datastream IRS series.

Swap rates are used to model two of the three measures of swap market volatility here examined: GARCH-based conditional volatility of daily changes and its low-frequency component extracted via curve fitting. The analysis focuses on the most liquid and relevant maturities – 2y, 5y, 10y and 30y – to capture the structure and the dynamics of the swap curve preserving useful information embedded in different tenors.

The third measure of swap market volatility is derived from swaptions, that is, options granting the right to enter into an interest rate swap at a predetermined fixed rate. Since swaptions embed market expectations about future swap rates' fluctuations, their prices provide implied volatilities (IVs). For this study, daily swaption data were sourced from Bloomberg, following the same crtieria of liquidity and market relevance described to selected swap rates. Specifically, a set of commonly traded expiry-tenor combinations – 1M1Y, 3M2Y, 3M5Y, 6M5Y, 1Y10Y, and 3M30Y – was collected. In this notation, the first element denotes the option's expiry (the forward horizon at which the option matures), while the second denotes the tenor of the underlying swap (the maturity of the IRS contract). For example, a 3M10Y swaption is an option to enter a 10-year swap contract in three months. Short-expiry, short-tenor contracts capture near-term monetary policy uncertainty, while long-expiry, long-tenor swaptions embed expectations about long-run macroeconomic fundamentals. The chosen set corresponds to the most liquid and representative contracts across maturities, ensuring coverage of both the short end and the long end of the interest rate curve. The underlying floating rate of the IRS is aligned with the one of the swap rates collected to model realized vol.

Data availability for swaptions is naturally shorter, as these "2nd degree" derivatives emerged only after the significant growth in swap market volumes – JPY, offers the earliest availability of swaption data, starting in 2006. The daily IVs are quoted in basis points (bps) of Normal Volatility, following the Bachelier model, which, unlike the Black (lognormal) model, does not explode in handling negative underlying rates, thus has been preferred, considering the negative interest rates policies adopted in the Eurozone (2014-2022) and in Japan (2016-2024).

3.2. Macroeconomic Uncertainty

Macroeconomic uncertainty has been approximated through a broad set of variables, modelling economic indicators, market-based measures, news-based indices and exchange rates.

Monthly, seasonally adjusted historical data on CPI, Core CPI, Industrial Production, Unemployment, and Consumer Confidence were collected for the three markets as well as daily data for EURUSD, EURJPY and USDJPY exchange rates[1]. The uncertainty of each variable was then quantified by modeling its volatility.

The study also includes the CBOE Volatility Index (VIX) and the Merrill Lynch Option Volatility Estimate (MOVE): the VIX reflects implied volatility in the US equity market, derived from 1-month S&P 500 options, while the MOVE is its fixed-income counterpart, capturing expected volatility in US Treasury yields.

Lastly, the news-based Economic Policy Uncertainty (EPU) indices developed by Baker, Bloom and Davis (2016) and their categorical extensions (Baker, Bloom, Davis & Kost, 2019; Baker, Bloom, Davis & Sammon, 2020) were examined to add another dimension to the assessment of macroeconomic risk, capturing the "risk sentiment" reflected in relevant press coverage. Specifically, EPU and Monetary Policy Uncertainty (MPU) indices were retrieved from Bloomberg for all three markets under study, with the exception of the euro area, for which no MPU index is available. In addition, the Global EPU index, both current-price-weighted and PPP-adjusted, was included to account for worldwide policy-related uncertainty.

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[1] For the US, Michigan Consumer Sentiment was included as a survey-based indicator of macroeconomic uncertainty. For the Euro area, HICP and Core HICP replaced CPI and Core CPI, reflecting the ECB's official benchmark and its harmonised methodology.

The selection of these variables is intended to provide a realistic empirical representation of the inherently abstract notion of macroeconomic uncertainty, reflecting those considered more relevant in prior studies (Azad et al. 2011; 2012; Tillman 2020; Sarisoy 2023; 2024). The proxies span fundamentals, surveys, policy indices, and market-based measures, capturing the different facets of uncertainty rather than overweighting a single dimension (Altig et al. 2020; Cascaldi-Garcia et al. 2023).

3.3. Regimes separation

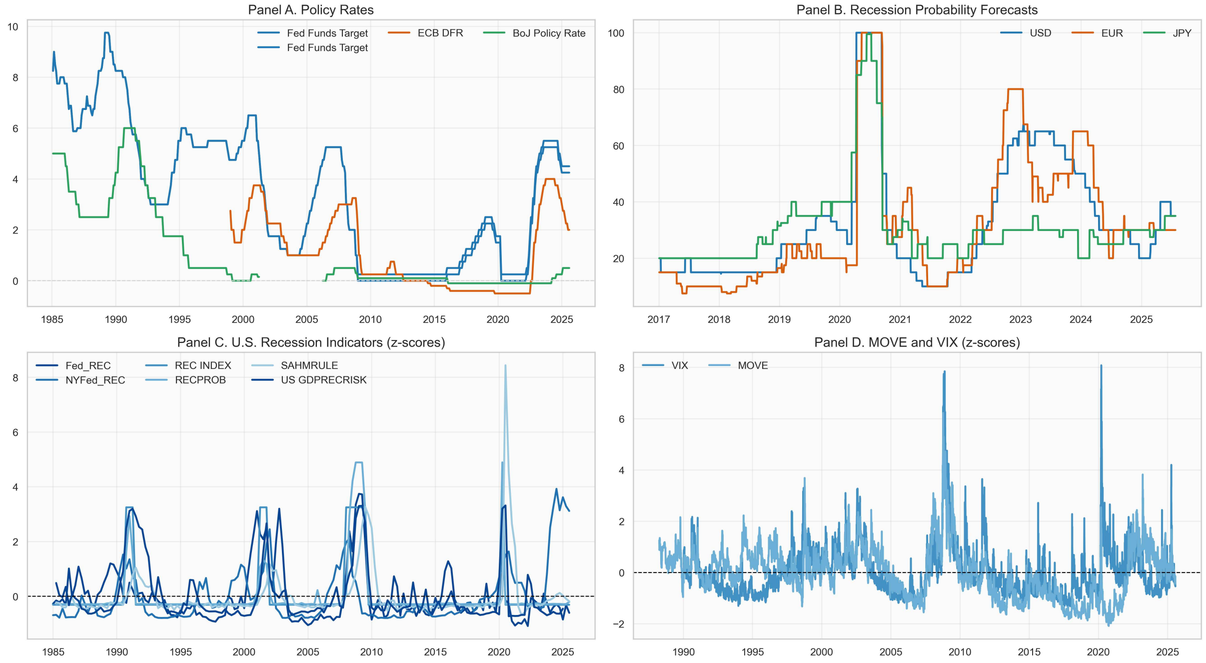
To distinguish between different risk and monetary policy regimes when analyzing the relationship between swap volatility and macroeconomic uncertainty, this study incorporates a comprehensive set of recession and policy indicators across the three economies under consideration. Monthly data from FRED include the Federal Reserve Recession Probability Index, the New York Fed recession probability measure, and the Sahm Rule indicator, complemented by quarterly GDP-based probabilities. Bloomberg data add recession probability forecasts for USD, EUR, and JPY, as well as a binary US recession signal.

To capture the monetary stance over time, central bank policy rates were collected for each region: the Federal Funds target rate (upper and lower bounds) for the US, the ECB Deposit Facility Rate for the Euro Area, and the BoJ policy rate for Japan. This setup enables a regime-based classification that integrates market- and survey-based recession probabilities, labor market signals, and GDP-based assessments of economic risk, while policy rates reflect the monetary response to those risks.

Figure 2 shows the key policy rates, recession risk measures, and the VIX and MOVE indices that form the basis to construct the macro regimes, capturing both recession risk and monetary policy cycles.

Figure 2. Policy Rates, Recession Risk, and Market Uncertainty

This figure presents the key macro regime indicators across four panels. Panel A plots the main policy rates for USD (Fed Funds Target Rate), EUR (ECB Deposit Facility Rate), and JPY (BoJ Policy Rate). Panel B shows Bloomberg recession probability forecasts for the three markets. Panel C reports a range of US recession indicators standardized to z-scores, including the Sahm Rule, REC Index, and GDP recession risk measures. Panel D displays standardized levels of the MOVE and VIX indices.



4. Methodologies

This section outlines the data processing procedures and methodologies employed to construct the dependent and independent variables, model their volatilities and extract low-frequency components through curve fitting, run correlation analysis and Granger causality tests and to ultimately evaluate the predictive power of swap market volatility for one-month-ahead macroeconomic uncertainty.

4.1. Data Processing

The collected series were transformed to obtain monthly series of macroeconomic variables volatility (dependent variables) and swap rates volatility (independent variables).

Macroeconomic variables were transformed to obtain stationary series suitable for volatility modelling, while preserving economic interpretability. For inflation series, standard year-on-year (YoY) rates have been computed from CPI and Core CPI indices, to then calculate monthly differences in these YoY rates as inputs for volatility estimation. Unlike earlier studies (Azad et al. 2011; 2012), which modelled volatility on monthly changes in raw CPI levels, this approach emphasizes the persistence of inflation trends rather than short-term price fluctuations. Using YoY inflation ensures consistency with official releases, inflation expectations, and central bank policy targets, while also addressing the non-stationarity of CPI levels confirmed by ADF tests.

Unemployment uncertainty was treated similarly, with volatility estimated on monthly changes in the unemployment rate, maintaining methodological consistency across variables.

Industrial production, by contrast, is stationary in levels and cyclical in nature, so monthly log growth rates were used directly.

For survey-based indicators such as consumer confidence and sentiment, monthly differences were preferred, since index levels can be negative in some regions (e.g., Europe), making growth rates less interpretable.

Exchange rates were modeled with daily log returns, consistent with financial market practice, while swap rates were expressed in daily differences rather than percentage changes to avoid distortions from negative denominators.

4.2. Time Series Diagnostic

Before estimating volatilities, each transformed series was examined for three key properties: stationarity, autocorrelation, and volatility clustering. These checks ensure the series are suitable for volatility modelling and help determine the appropriate model specification.

Stationarity: Stationarity was tested using the Augmented Dickey-Fuller (ADF) test, the standard tool for detecting unit roots. Results strongly reject the null of non-stationarity across all processed series, confirming their suitability for volatility analysis. Full statistics and p-values are reported in Table 2 of the Appendix.

Autoregressive Structure (AR effects): The presence of autocorrelation – i.e., the extent to which current values of a series are correlated with its past – was assessed through the Ljung–Box test. The test evaluates the joint null hypothesis of no autocorrelation across a specific range of lags. Significant AR effects were found in daily swap rate changes and in most macroeconomic series, while some (e.g., EURUSD daily returns, Japanese IP, US unemployment and consumer confidence) displayed little or no autocorrelation. These results informed both the specification of the mean equations in the GARCH models and the data treatment when constructing rolling volatilities, where series were “demeaned” to remove predictable components before estimating the variance. Full statistics and p-values are reported in Table 3 of the Appendix.

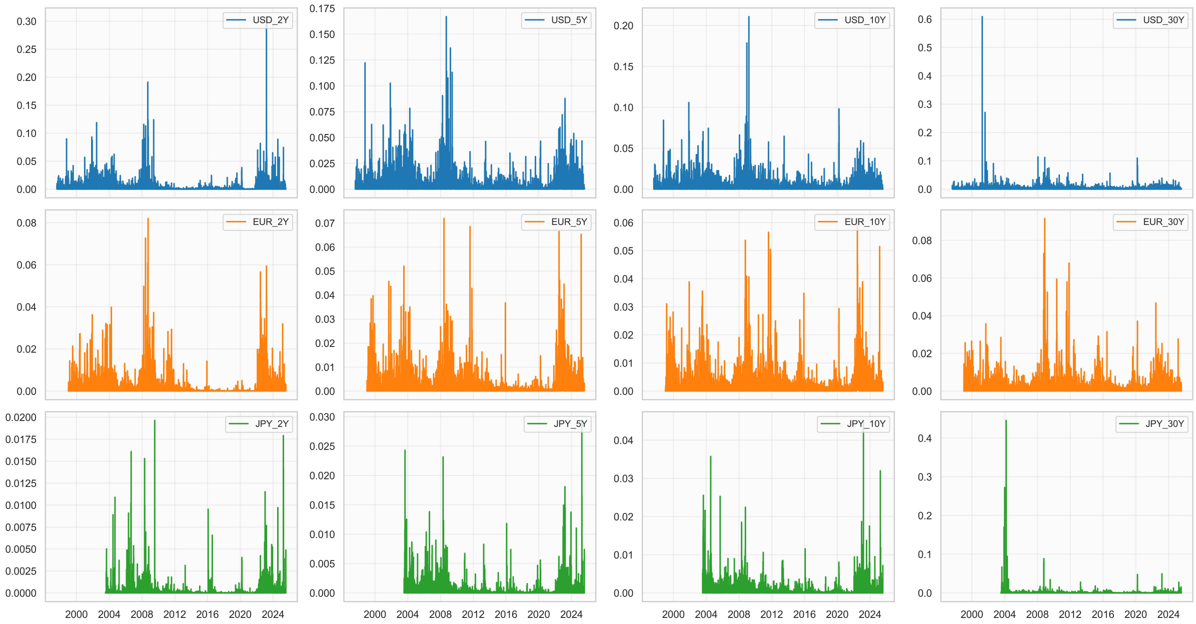
Volatility Clustering: Financial and macroeconomic time series often display volatility clustering, whereby large shocks are followed by large shocks and small shocks by small shocks, generating periods of persistently high or low volatility. Econometrically, this corresponds to conditional heteroskedasticity, meaning that the variance of the series is time-varying rather than constant.

To visualise explicitly visualise this phenomenon, Figure 3 plots the squared residuals of daily swap rate changes across maturities. Here, residuals are defined as deviations of each series from its mean (the unexplained component of a simple constant mean model).

Periods of relative calm alternate with bursts of large fluctuations reflect the tendency of these series to persist in regimes of high and low volatility. This visual evidence motivates the employment of formal tests to assess heteroskedasticity's statistical significance.

Figure 3. Squared residuals of daily swap rate changes

This figure plots squared residuals of daily changes in swap rates across maturities (2Y, 5Y, 10Y, 30Y) for USD, EUR and JPY. The squared series highlight the presence of volatility clustering by amplifying periods of large shocks, which provides the statistical foundation for testing conditional heteroskedasticity using the ARCH LM test.



The ARCH framework provides a statistical way to test for this by examining autocorrelation in squared residuals. Specifically, the ARCH Lagrange Multiplier test (Engle, 1982) does not test volatility clustering per se, but rather conditional heteroskedasticity in the form of ARCH effects, i.e. whether past shocks explain current variance. Rejection of the null indicates that volatility is time-varying and predictable, which is consistent with the empirical phenomenon of volatility clustering observed in financial and macroeconomic series.

Results indicate that all swap rates and exchange rate daily changes, as well as most macroeconomic monthly series, exhibit statistically significant ARCH effects, justifying the use of GARCH models to capture their conditional volatilities. Conversely, USD unemployment, sentiment and confidence, JPY inflation and core inflation, and EUR confidence failed to reject the null of homoskedasticity. For these series, volatility clustering is not statistically supported and GARCH models would not improve volatility estimation. Instead, rolling-window measures are employed to quantify their uncertainty, thereby maintaining methodological consistency while avoiding unnecessary model complexity. Table 4 in the Appendix reports the full set of test statistics and p-values from the ARCH LM test.

4.3. Volatility Modelling

The volatility of swap rates, exchange rates, and macroeconomic indicators is modelled using approaches tailored to the statistical properties and frequency of each series. High-frequency financial data provide a large number of observations and display pronounced volatility clustering, rapid responses to shocks, and relatively fast mean reversion. In contrast, lower-frequency macroeconomic data are structurally different: monthly indicators have muh smaller samples, suffer from data quality issues such as measurement errors and consequent revisions and, most importantly, exhibit highly persistent shocks, with their volatilities showing a "long memory" component. Given these properties[2], a careful approach is implemented for macroeconomic data.

The Generalized Autoregressive Conditional Heteroskedasticity (GARCH) framework, introduced by Bollerslev in 1986 as an extension of Engle's (1982) ARCH model, is adopted here as the benchmark approach for both financial and macroeconomic since it captures conditional heteroskedasticity and volatility persistence, features that were detected in nearly

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[2] The limitations of handling macroeconomic data volatility are well recognized in the literature. Bloom (2009) emphasizes that macro indicators are too infrequently measured and heavily revised to capture short-term uncertainty shocks, which is why the author proxies uncertainty with financial market volatility instead. Jurado, Ludvigson, and Ng (2015) similarly argue that equating uncertainty with conditional volatility can be misleading in macro contexts, proposing instead a measure based on forecast error variances across a broad set of indicators. These contributions highlight that while GARCH remains a tractable and widely used benchmark, it should be complemented with robustness checks and interpreted cautiously when applied to monthly macroeconomic data.

all series through ARCH–LM tests. However, because GARCH estimation on macro series can be sensitive to sample size, revisions and extraordinary persistence of shocks, complementary rolling-window volatility measures are also computed as robustness checks.

Specifically, GARCH captures conditional heteroskedasticity by allowing the variance to depend on q past shocks and p past variances. In practice, a GARCH(p, q) model consists of two components: a mean equation, which specifies the dynamics of the series itself, and a variance equation, which governs the evolution of volatility.

The mean equation is given by:

$$y_t = \mu + \sum_{i=1}^{k} \phi_i y_{t-i} + \varepsilon_t \quad \text{with } \varepsilon_t \sim i.i.d.(0, \sigma_t^2)$$

where y_t is the series of interest, μ is a constant mean, and autoregressive terms ϕ_i capture dependence on past values.

While, the variance equation follows the process:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2$$

where α_i represent the short-run impact of past shocks q (ARCH effects), β_j measure persistence of past volatility p (GARCH effects), and the sum $\alpha+\beta$ indicates the degree of persistence in volatility. When $\alpha+\beta$ is close to one, shocks to volatility decay very slowly, consistent with the interpretation of macroeconomic uncertainty as a highly persistent regime rather than a transitory spike. In this study, to account for the heavy tails often observed in financial and macroeconomic time series, innovations are modelled using a Student-t distribution rather than assuming normality.

Model adequacy was assessed in two steps. First, alternative GARCH specifications were compared using the Akaike Information Criterion (AIC), which rewards goodness of fit while penalizing excessive parameterization. Specifications with lower AIC values were preferred, as they indicate better fit without unnecessary overfitting.

Second, the adequacy of the selected model was validated through residual diagnostics. Standardized residuals were tested for remaining ARCH effects using the ARCH–LM test on squared residuals, while the Ljung–Box test on raw residuals confirmed the absence of autocorrelation in the mean equation. The persistence ($\alpha+\beta$) was examined to ensure the volatility is mean-reverting rather than explosive. The final specification for each series is chosen to balance goodness of fit, parsimony, and interpretability.

The selected GARCH specifications and their corresponding fit diagnostics are reported in the Appendix: Table 5 presents the results for daily swap and exchange rate volatility, while Table 6 displays macro indicators’ specifications.

Daily Financial Data

For daily swap rate changes and exchange rate returns, modelling GARCH volatilites has been relatively straightforward. These series exhibit strong volatility clustering, large sample sizes, and well-behaved persistence patterns.

As robustness check, 20-day rolling window standard deviations were also computed. The volatility comparison, illustrated in figures 4 and 5, exhibits very similar dynamics, strenghtening consistency across models.

Figure 4. Swap Rate Volatility: GARCH vs 20-Day Rolling Estimates

This figure compares GARCH conditional volatilities (solid lines) with 20-day rolling standard deviations (dashed red lines) of daily swap rate changes across USD, EUR and JPY markets for maturities of 2Y, 5Y, 10Y, and 30Y. The rolling measures provide a simple, backward-looking proxy for short-term volatility, while the GARCH model captures conditional heteroskedasticity and persistence in volatility dynamics.

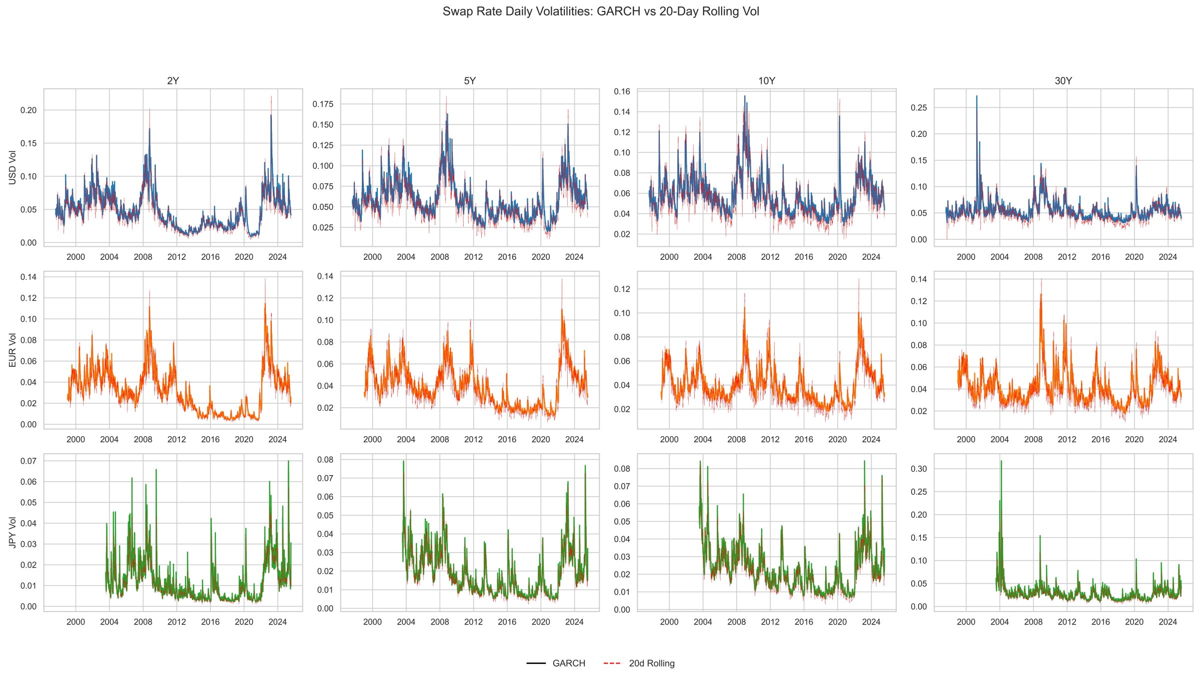
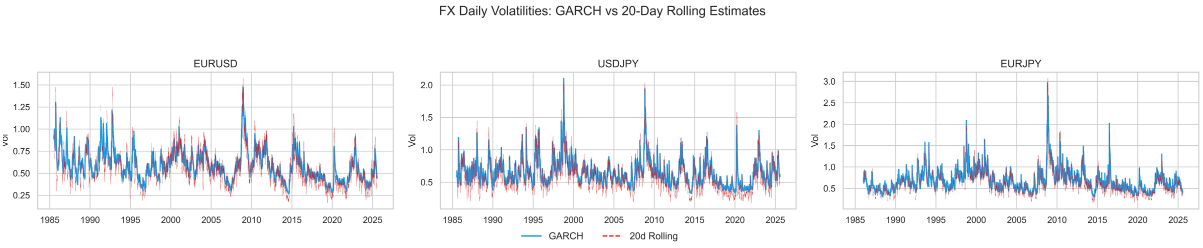


Figure 5. FX Volatility: GARCH vs 20-Day Rolling Estimates

This figure presents the same comparison for major FX pairs (EURUSD, USDJPY, EURJPY). GARCH volatilities (solid purple) and with 20-day rolling standard deviations (dashed red lines).



These daily volatility series of swap and exchange rates have been then aggregated to monthly frequency (squared root of monthly average variances) and standardised into z-scores to allow scale comparability with monthly macroeconomic volatilities.

Monthly Macroeconomic Data

Modelling macro series via GARCH revealed unstable persistence parameters and residual long-memory dynamics.

A wide range of GARCH models with varying lag structures in the mean and variance equations has been estimated, including the GJR-GARCH extension that allows for asymmetric effects of positive and negative shocks.

Comparing richer GARCH specifications and more parsimonious AR(k)–GARCH(1,1) models highlights a clear tradeoff. Richer models often achieved lower information criteria (AIC) and, in some cases, stronger out-of-sample prediction, but the resulting volatility series displayed counterintuitive dynamics, which seem following innatural periodical patterns. These unstable results reflect the tendency of over-parameterised models to overfit, forcing the conditional variance to absorb high-frequency autocorrelation and seasonal structure that should be treated in the mean equation. As a result, the estimated volatility captured spurious persistence rather than genuine uncertainty dynamics, reducing its economic interpretability[3].

Conversely, simpler specifications produced smoother and more stable volatility dynamics that aligned more closely to realistic uncertainty. Although these parsimonious models do not always outperform richer alternatives in forecasting metrics, they avoid overfitting, gain interpretability, and provide realistic proxies for macroeconomic uncertainty, which is central at this stage of the research to avoid relying on less rigorous, purely ad-hoc measures.

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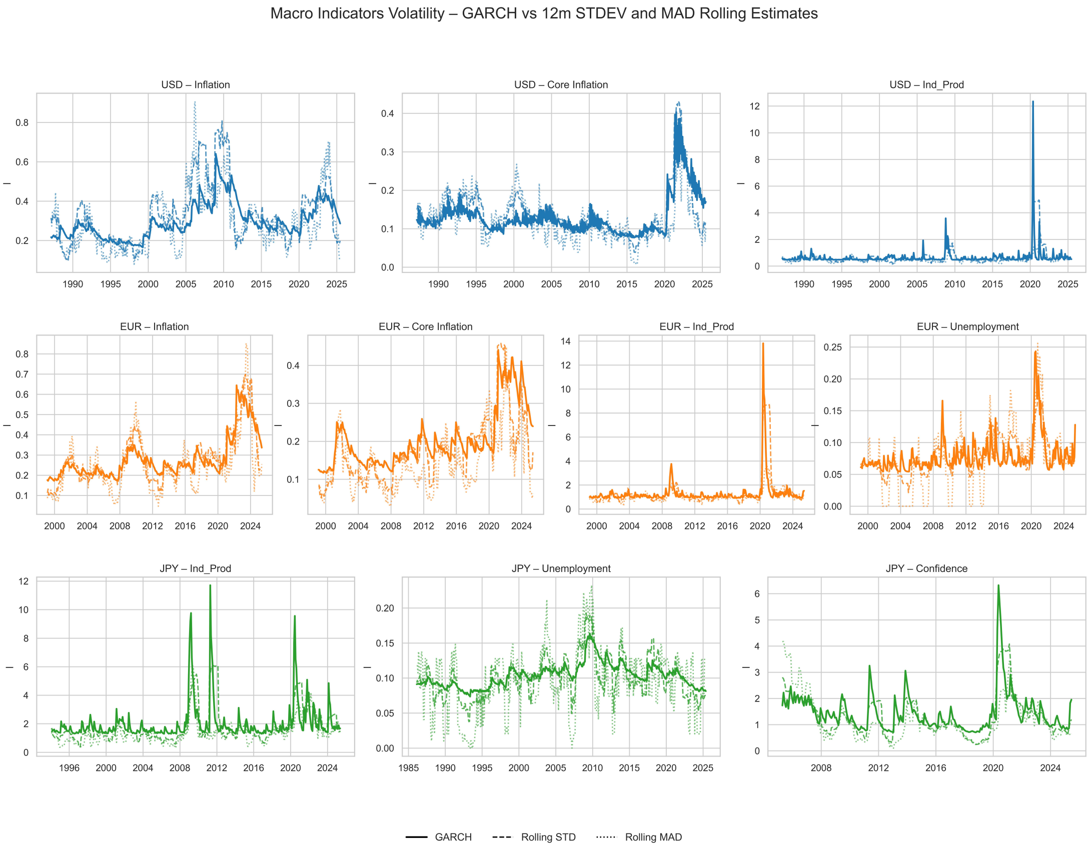
[3] These practical issues in applying GARCH models and the unstable results of complex specifications are well-documented in early studies, such as Zivot (2008), Practical Issues in the Analysis of Univariate GARCH Models; Doornik & Ooms (2008), Multimodality in GARCH Regression Models; and Hillebrand & Medeiros (2008), Structural Breaks and Long Memory in GARCH Models.

To address periodical patterns observed in plotting richer specifications, AR(1,12) terms were incorporated in the mean equation of each series. This adjustment filtered out short-run and seasonal autocorrelation, preventing such spurious cycles from contaminating the variance dynamics. In addition, for the unemployment and industrial production series, dummy variables for the Global Financial Crisis and COVID-19 were introduced to account for the exceptional impact of these shocks on these two real-economy fundamentals. These additions served as robustness refinements: while the dummies did not substantially alter the results, they ensured that the conditional variance estimates were not distorted or inflated by extraordinary events.

To test the stability of these GARCH estimates, complementary rolling-window realized volatilities, have been computed using both standard deviations and Median Absolute Deviation (MAD). Figures 6 presents the comparison between the three measures, providing a direct assessment of how alternative approaches differ in capturing the volatility of the same macroeconomic indicator.

Figure 6. Macro Indicators Volatility – GARCH vs 12m STDEV and MAD Rolling Estimates

This figure compares GARCH-based conditional volatilities with 12-month rolling measures (standard deviation and mean absolute deviation) for key macroeconomic indicators in USD, EUR, and JPY. The comparison highlights differences in how short-run fluctuations and longer-run persistence are captured.



The comparison reveals how GARCH volatilities provide an overall smoother and more persistent profile than rolling measures, filtering out much of the short-term noise that characterises standard deviation and MAD estimates. However, GARCH seems responding sharply, with pronounced volatility spikes, to large shocks to then retrace without inflating later volatility. The rolling standard deviation tracks GARCH fairly close, showing slightly noisier and less persistence estimates. Rolling MAD is even less persistent and tends to understate black-swan events, such as the Global Financial Crisis and Covid19. This considered, GARCH remains the benchmark specification whenever significant ARCH effects are detected, offering a more reliable framework to model persistent uncertainty than realized rolling volatilites.

Finally, to ensure that results were not mechanically driven and distorted by the extraordinary COVID-19 episode, the same GARCH specifications have been re-stimated on truncated samples ending in January 2020. The comparison shows that baseline dynamics remain almost unchanged until early 2020, after which the full-sample estimates rose sharply, reflecting the unique shock. This exercise confirmed that COVID-19 added volatility information without overturning the overall underlying volatility patterns. The side-by-side comparison of full-sample and truncated estimates is reported in Figure 7 of the Appendix.

Low Frequency Component in Swap Rate Volatility

Extracting the low-frequency component of swap rate volatility (LVOL) – the smooth, slow-moving trend in conditional variance – helps to clean short-term noise from the explanatory variable itself, ensuring that the series captures genuine and persistent uncertainty rather than transitory fluctuations. Noisy predictors risk to overstate short-run co-movements and dilute the structural relationship between financial markets and the macroeconomic uncertainty. Curve fitting on GARCH volatility series allows to obtain a cleaner volatility that better captures shifts in expectations about future macro risk, washing out very short term trading dynamics and technical effects. This produces a more interpretable and robust signal for a variable whose role in this study is to predict future macroeconomic uncertainty.

Specifically, a cubic spline function has been chosen to extract the low frequency component from swap rate volatilities.

A cubic smoothing spline is a flexible curve-fitting method that balances approximation accuracy with smoothness of the fitted curve, defined as:

$$\min_{f} \sum_{t=1}^{T} \left(y_t - f(t)\right)^2 + \lambda \int \left(f''(t)\right)^2 \, dt$$

where the first term controls the fit to the observed volatility series and the second penalizes excessive curvature of the fitted function, avoiding fit values too close to the observed ones. The smoothing factor λ governs the trade-off: low λ values allow the spline to track closer high-frequency fluctuations, while high λ values enforce smoothness, isolating the slow-moving, low-frequency component of volatility and filtering out noise more heavily.

The choice of the smoothing parameter λ is central, as it heavily influences both the shape of the fitted curve and the resulting correlation between the extracted low frequency volatility and macroeconomic uncertainty series. To illustrate this, Figure 8 of the Appendix plots the swap rate volatility series fitted with alternative smoothing factors, highlighting how the degree of smoothness can drastically alter the extracted signal.

Hence, rather than selecting a single λ ex ante or enforcing the same smoothing across all series, the regressions have determined which smoothing factor was most informative. Specifically, for each swap–macro vol series pair, LVOL is extracted under a range of many candidate λ values, and predictive regressions are estimated using each smoothed series as the explanatory variable. The smoothing factor that yields the strongest predictive relationship with the macro volatility target is then retained. This procedure ensures that the low-frequency volatility measure used in each regression is not imposed arbitrarily, but chosen in a way that maximizes its empirical relevance for capturing the underlying risk associations. The latter are considered more suitable for capturing underlying volatility dynamics and extracting reliable predictive signals.

The use of slow-moving measures of swap rate volatility is motivated by earlier work in the literature, most notably Azad, Fang, and others (2012), who introduced the Asymmetric Spline GARCH (ASP-GARCH) model of Rangel and Engle (2012) to decompose conditional volatility into high- and low-frequency components. Their results showed that the low-frequency component of swap rate volatility is significantly more related to macroeconomic uncertainty than the observed GARCH conditional volatility, highlighting the importance of persistent volatility regimes in dealing with macroeconomic frameworks. While ASP-GARCH provides a rigorous parametric framework, it requires heavy computational implementation, complex tuning of the parameters and strong distributional assumptions.

In this thesis, a more transparent and robust alternative has been adopted by fitting a cubic spline to GARCH conditional volatility series. This approach preserves the core idea of isolating a slow-moving volatility component to test its association with persistent macro uncertainty, while avoiding the complexity and fragility of full ASP-GARCH estimation.

All model-free volatility measures considered in this study, not presented in this paragraph, which include swaption-implied volatilities, VIX, MOVE, and policy uncertainty indices, are presented in Figures 9, 10, and 11 of the Appendix.

4.4. Correlation Analysis

After modelling both the explanatory variables (swap rate volatilities) and the dependent variables (macroeconomic uncertainty measures), a natural first step in analysing their relationship is a comprehensive correlation analysis. This stage highlights which macro variables are most strongly linked to swap volatility, whether relationships differ across currencies and maturities, and whether the dynamics appear contemporaneous or lagged. It also offers an initial diagnostic of stability over time, helping to interpret and contextualise the results from more demanding econometric frameworks.

Three complementary approaches are implemented. First, classic Pearson correlation matrices are computed across all variables, providing a static overview of contemporaneous time-series associations. Second, lagged correlations are estimated over a 12-month horizon, revealing either potential predictive structures or spurious correlation rising mechanically from common persistence rather than true forecasting content. Third, rolling and expanding correlations are used to assess stability over time: rolling windows capture short- to medium-term dynamics, while expanding windows show how overall correlations evolve as additional observations are incorporated.

These methods jointly provide descriptive evidence on the strength, persistence, and time variation of the relationship under study. At the same time, correlation coefficients do not establish causality: strong contemporaneous or lagged correlations may simply reflect common shocks or shared persistence rather than genuine directionality. Hence, correlation analysis is used as a preliminary diagnostic, a first look at the nature of this relationship, which must be explored further through Granger causality tests and predictive regression models that explicitly assess directionality and predictive power.

4.5. Granger Causality Tests

Following the descriptive evidence from the correlation analysis, the next step is to examine whether the relationship between swap market volatility and macroeconomic uncertainty displays systematic lead–lag dynamics, and in which direction these operate. Granger causality tests assess whether lagged values of swap volatility add explanatory power for the current level of macro uncertainty beyond what is contained in its own past, and vice versa. The tests are implemented with bivariate vector autoregressions (VARs), estimated separately for each swap-macro vol pair, with the lag order *l* of both variables selected by the Bayesian Information Criterion (BIC) to ensure a parsimonious and data-driven choice of memory depth.

Formally, the system can be written as:

$$Y_t = \alpha_Y + \sum_{\{i=1\}}^{p} \delta_i Y_{\{t-i\}} + \sum_{\{i=1\}}^{p} \beta_i X_{\{t-i\}} + u_t$$

$$X_t = \alpha_X + \sum_{\{i=1\}}^{p} \delta_i X_{\{t-i\}} + \sum_{\{i=1\}}^{p} \beta_i Y_{\{t-i\}} + v_t$$

Running the tests in both directions is crucial as theory, empirical evidence, and prior literature all suggest strong two-way linkages. Swap market volatility may embed forward-looking expectations about future economic conditions, while at the same time responding sharply to realized shocks; similarly, economic uncertainty indices, data releases and, in general, future macro risk may reflect the volatility already priced in financial markets. To capture this interaction, the test evaluates whether past values of one variable significantly improve the fit of the other. Statistical significance is determined by rejecting the null hypothesis that jointly the past observations of one variable provide no incremental information for the other, beyond what is already contained in its own autoregressive history.

Since this study is specifically oriented toward assessing the predictive power of swap rate volatility for macro uncertainty, a directional Granger causality score (NetGC) has been constructed. This metric combines the statistical strength of the predictive content from swap volatility to macro uncertainty with an adjustment for predictive feedback in the opposite direction. It highlights cases where swap markets provide genuine forward-looking information, rather than situations where both series simply co-move or explain each other.

Formally, the score is defined as:

$$NetGC(X \rightarrow Y) = -\ln\left(p_{\{X \rightarrow Y\}}\right) + \lambda \ln\left(p_{\{Y \rightarrow X\}}\right)$$

where $p_{\{X \rightarrow Y\}}$ and $p_{\{Y \rightarrow X\}}$ are the p-values from the Granger tests in each direction and λ is a penalty parameter, set to 1 in the baseline so that forward and reverse directions receive equal weight. A lower p-value for $X \rightarrow Y$ increases the score, while predictive feedback from $Y \rightarrow X$ reduces it. This score is then used to rank the most informative predictors across volatility measures (swaption implied volatility, GARCH conditional volatility, and low-frequency smoothed volatility), currencies and maturities. The strongest candidates identified by NetGC are subsequently examined in tailored regression frameworks, allowing a deeper assessment of their predictive content.

4.6. Predictive Power Evaluation

Following the Granger causality analysis, the final step is to assess the true predictive performance of swap volatility for macroeconomic uncertainty in-sample (IS) and out-of-sample (OOS). From the previous stage, the 25 strongest swap-macro volatility pairs (by NetGC score) were retained within each currency and for each volatility type – swaption implied volatility and swap rate GARCH volatility (both the original and its low frequency component). This filtering brings to the next stage 150 pairs in total, ensuring to evaluate the most informative predictor–target relationships identified in the causality analysis, rather than relying on arbitrary selection.

For each selected predictor-target pair, a lagged regression model has been constructed with a one-month forecast horizion. The dependent variable ($Y_{(t+1)}$) is a series of macroeconomic uncertainty, while the predictor block $(X_t, X_{t-1}, \ldots, X_{t-i})$ represents lagged values of a swap market volatility series. The candidate set of lags C includes the optimal lag order identified by the VAR–BIC Granger causality tests and the single strongest lag from univariate regressions of X_t on $Y_{(t+1)}$.

From the pool of candidate lags, the number of past observations of the predictor was further reduced using LASSO regression. LASSO (Least Absolute Shrinkage and Selection Operator) applies an *L1* penalty on the regression coefficients, which leads irrelevant or weak predictors to converge to zero. Here LASSO pre-selects relevant lags of swap volatility discarding redundant ones, before running OLS regressions. This procedure prevents against overfitting and ensures parsimony, so that the predictive power attributed to swap vol reflects genuine information rather than noise or excessive persistence. LASSO estimator works on the beta coefficients as:

$$\hat{\beta} = argmin_{\beta} \sum (t = 1)^T \left(Y_{(t+1)} - \alpha - \sum (i \in C) \beta_i X_{(t-i)}\right)^2 + \lambda \sum (i \in C) |\beta_i|$$

The first term minimizes the sum of squared residuals, while the second term, the *L1* penalty $\lambda \sum (i \in C) |\beta_i|$ shrinks coefficients toward zero. As λ increases, more coefficients are forced to zero, effectively performing variable selection among the candidate lags of the predictive series under analysis.

Given the strong persistence of macroeconomic volatility series, it is essential to benchmark predictive regressions against an autoregressive baseline. Macro uncertainty is inherently tenacious, having the tendency to cluster and decay only slowly over time. Regressing macroeconomic volatility solely on swap rate volatility might return misleading results, as any apparent predictive power could simply reflect persistence in macro risk, rather than genuine information in swap volatilities. To avoid this "overstated predictability", the predictive content is evaluated incrementally, relative to an autoregressive benchmark[4].

The main specification to evaluate swap volatility contribution is therefore an ARX model, in which each proxy of macro risk is regressed on its own first lag (AR(1)) and on the subset S of each swap volatility series' lags $(X_t, X_{t-1}, \ldots, X_{t-i})$ selected by LASSO:

$$Y_{t+1} = \alpha + \delta Y_t + \sum_{i \in S} \beta_i X_{t-i} + u_t,$$

Two complementary specifications are estimated alongside the main ARX benchmark to assess robustness. First, an "X-only" model regresses macro uncertainty exclusively on the selected lags of the independent variable, omitting the autoregressive term Y_t. This serves as sanity check since, by construction, such a model is expected to have low explanatory power, since it ignores the strong persistence of the dependent variable. Its role is therefore not to compete with the ARX specification, but to verify that any incremental predictive content of swap market variables is not an inflated by overfitting in a persistent series.

Second, a PCA-ARX model is implemented, in which the selected lags of the swap volatility series are compressed into a small number of principal components (PCs). Since adjacent lags of a persistent predictor are typically highly correlated, including many of them directly in the regression risks inflating multicollinearity and obscuring the real source of predictive power.

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[4] In contrast with the asset-returns predictive literature (e.g., Goyal and Welch 2008; Rapach and Zhou 2013), which typically employs the historical average as a benchmark, this study adopts an autoregressive AR(1) benchmark to better account for the strong persistence of macroeconomic volatility series. This choice is further motivated by Ludvigson, Ma, and Ng (2021), that show how macroeconomic uncertainty is often an endogenous response to macro shocks, implying that past volatility itself is a powerful predictor of future uncertainty.

Principal component analysis (PCA) addresses this by extracting orthogonal linear combinations of the lagged predictors that capture the maximum common variance shared by different lags. Here, the first two components have been considered: PC1 captures the dominant common variation (level), while PC2 captures the secondary orthogonal source of variation (slope). The predictive regression is then re-specified as:

$$Y_{t+1} = \alpha + \delta Y_t + \beta_1 PC1_t + \beta_2 PC2_t + u_t$$

This dimensionality reduction both mitigates multicollinearity and clarifies whether predictive edges come from latent common factors rather than from specific lagged terms. However, this gain in parsimony and stability comes at the cost of interpretability, since the principal components are synthetic factors and cannot be mapped back directly to the effect of a single lag. PCA is widely and commonly applied in settings with many distinct predictors (mulitvariate regressions), here it is used across multiple lags of a single predictor, which is unconventional but may provide a useful robustness check.

In-sample OLS regressions are estimated in two complementary ways.

First, pooled regressions with regime fixed effects are estimated across the full sample. This specification maximises the number of observations and provides a stable benchmark, while allowing intercepts to shift across regimes. By absorbing these mean shifts, the pooled model highlights whether predictors carry stable incremental information once structural breaks are controlled for. Macroeconomic risk regimes have been defined observing the co-movement of alternative recession risk indicators, as described in the Data session of this thesis.

Second, fully separate regressions are run within regimes. This explicit regime separation allows beta coefficients to evolve consistently across different moments of the economic cycle and interest rate environments.

This dual strategy ensures both efficiency and flexibility: full-sample regressions preserve statistical power, giving baseline inference, while regime-specific regressions track betas evolution across economic states, highlighting the time-varying properties of the risk transmission between swap market and macroeconomics.

To assess the real predictive power, the described models have been eventually evaluated out-of-sample (OOS). Rather than splitting the full sample into fixed in-sample (IS) and OOS periods with a cutoff date, an expanding window approach has been adopted. At each t point, the model is re-estimated using all available data up to t, and used to predict $t + 1$. The window then expands step by step, ensuring that, at each step, forecasts are made using only information available in real time, avoiding look-ahead bias. This avoids arbitrary choices of a cutoff date, which can strongly influence results in relatively short samples (monthly data), and provides a more realistic evaluation of forecasting performance as it evolves over time, allowing the analysis to trace whether predictive power strengthens or weakens across different economic regimes.

The OOS performance of the two specifications, ARX and PCA-ARX, is evaluated as the incremental OOS R-Squared relative to the AR(1) benchmark. Referring to the ARX specification, the R_{OS}^2 is so defined:

$$R_{OS}^2 = 1 - \frac{MSE\left(\widehat{Y^{ARX}}\right)}{MSE\left(\widehat{Y^{AR}}\right)}$$

Where the Mean Squared Error (MSE) is:

$$MSE(\hat{Y}) = \frac{1}{N}\sum_{t=1}^{N}\left(Y_{t+1} - \widehat{Y_{t+1}}\right)^2$$

R_{OS}^2 measures the proportional reduction in forecast errors of the predictive model relative to a benchmark[5]. A positive R_{OS}^2 here indicates that swap-based predictors improve forecast accuracy compared to the AR(1) benchmark, while negative values imply deterioration.

The strong persistence of macroeconomic volatility series led to favour an autoregressive baseline over the historical-mean benchmark commonly used in returns predictability studies. This makes the framework more conservative: only clear and consistent improvements over the autoregressive model are taken as evidence of genuine predictive content. A constant-mean forecast would be inadequate in this context, since macro uncertainty is highly persistent and mean-reverting only over long horizons. By contrast, the AR(1) captures this persistence parsimoniously, typically explaining a large share of the variance in macro volatility. This sets a high bar for validation: if swap market variables outperform the AR(1) benchmark, their information content can be interpreted as a genuine forward-looking signal rather than a statistical artifact of persistence.

To ensure that forecast gains are not due to chance, two complementary tests are applied. The Clark–West (2007) test adjusts for the fact that ARX models are built on the AR benchmark, preventing spurious rejections in favor of the more complex model. The Diebold–Mariano (1995) test compares forecast error series from competing models, evaluating whether differences in mean squared errors are statistically significant.

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[5] The out-of-sample R-Squared follows the forecasting evaluation framework of Goyal and Welch (2008) and Campbell and Thompson (2008). The key difference in this study is the employed benchmark: instead of the historical average, the benchmark is an autoregressive model.

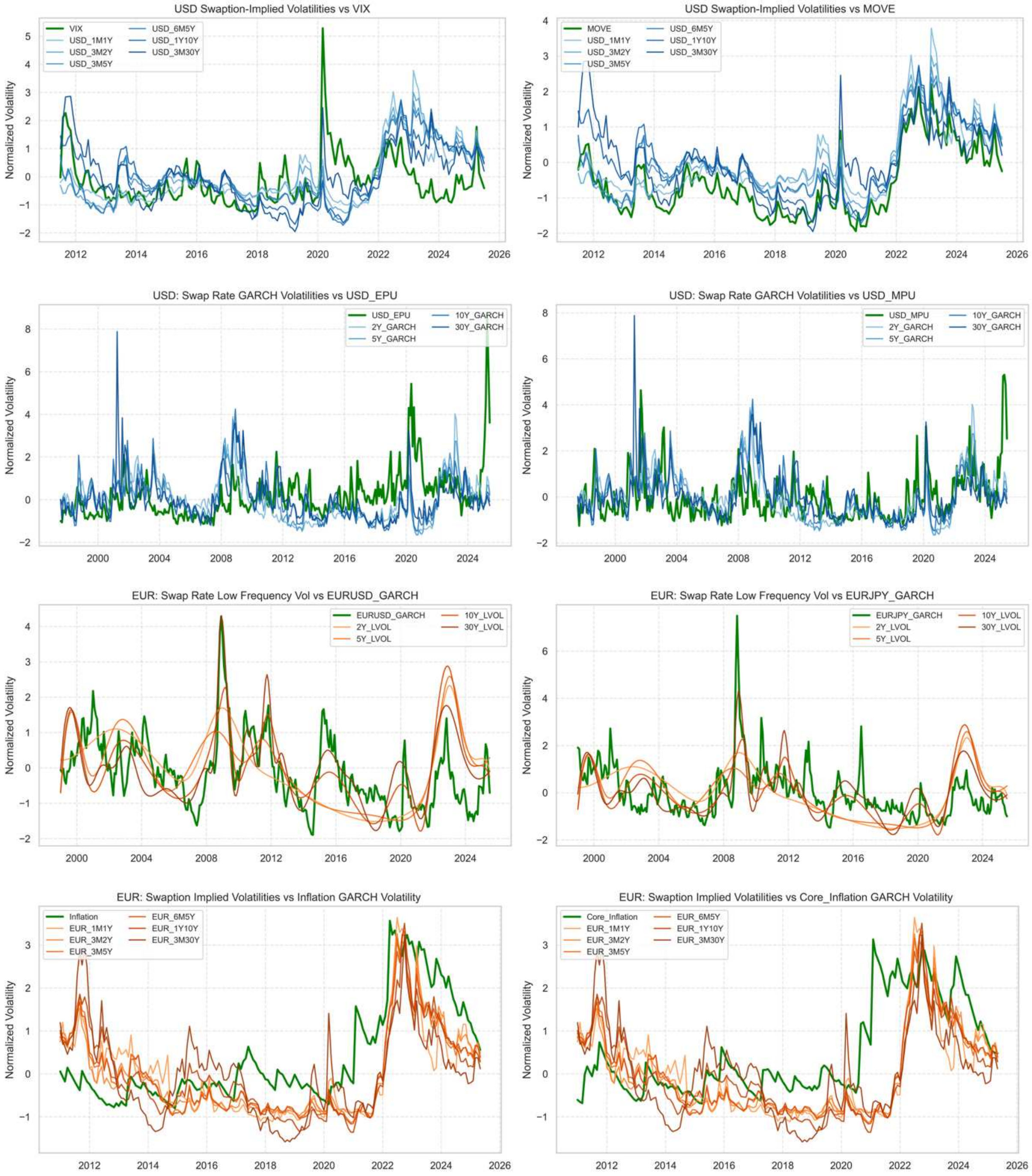
5. Results

5.1. Visualisation

An initial visual inspection of the data reveals a strong co-movement between swap volatility and several measures of macroeconomic risk, as illustrated in Figure 12. Notable alignments emerge with inflation and core inflation volatility, macroeconomic policy uncertainty (MPU) indices, exchange rate volatility, and market-based uncertainty indicators such as the MOVE. Both implied volatility from swaptions and conditional GARCH volatility extracted from swap rates display meaningful connections with macro risk.

A particularly striking case is the divergent association of USD swaption IVs with the MOVE and VIX indices. Short-term swaption Ivs track the MOVE index almost perfectly, while the co-movements with VIX diverges, especially in recent times post 2022 shocks. The difference reflects the informational content of these indices: the MOVE is essentially the “Bond Market VIX”, pricing near-term interest rate uncertainty and central bank policy risk, hence sharing with short term swaption IV the same underlying latent factor. By contrast, the VIX is driven by equity-specific factors, sharing only the broad risk sentiment component with swaption implied vol, and not the pure rates volatility components.

Figure 12. Swap Market Volatility and Macroeconomic Risk Co-Movements



5.2. Correlation Structure

The preliminary visual evidence motivates a systematic correlation analysis, which provides central descriptive evidence on the strength and persistence of linkages between swap market volatility and macroeconomic uncertainty ((see Figure 13, 14 and 15 in the Appendix for the full set of results across markets).

Full-sample correlation matrices reveals moderate to strong associations. Notably, inflation volatility reaches correlations around 0.5-0.75 with EUR swap volatilities; news-based policy uncertainty indices display overall strong correlation across markets (0.4 – 0.55), FX volatilities exhibits high correlation overall with the respective markets (0.5 to 0.7); market-based indices, in particular the MOVE, display the strongest associations, while correlations with real activity indicators of growth and labour markets (industrial production, unemployment) are weaker and less stable across tenors and currencies.

Rolling- and expanding-window estimates further reveal that correlations are anything but static. Inflation-related uncertainty has become more tightly linked to swap volatility in the post-2020 environment, especially at longer tenors, while the relationship with policy uncertainty indices tends to spike episodically around central bank turning points. FX volatility, once closely aligned with rate volatility, has increasingly disassociated in recent years as currency markets have been driven by idiosyncratic geopolitical shocks and policy divergence. Across measures, smoothed low-frequency volatility (LVOL) consistently displays stronger and more persistent co-movement with macro uncertainty than raw GARCH estimates, reinforcing the interpretation that structural, slow-moving forces rather than transitory shocks underpin the relationship between swap markets and macroeconomic risk.

Taken together, these dynamics suggest that the informational role of swap market volatility has evolved over time. In the post-pandemic, high-inflation environment, swap volatility has increasingly embedded forward-looking information about macro price uncertainty, particularly at longer maturities where term structure risk is most exposed to inflation expectations. By contrast, the relationship with real activity indicators such as industrial production and unemployment remains weaker and more episodic, with rolling correlations often fluctuating around zero and lacking sustained patterns. The rolling two-year window analysis is crucial here: it isolates the recent surge in predictive strength that would otherwise be diluted in full-sample or expanding-window averages.

This finding highlights a structural shift: swap market volatility has become tightly intertwined with macroeconomic uncertainty, most notably with inflation risk, in a way not seen before the post-pandemic regime. The strengthening of this links is the central motivation of this thesis, raising the fundamental question of whether interest rate markets merely react to uncertainty or actively embed forward-looking information about future macroeconomic risk, in such interesting times for the entire economy. Figures 16 and 17 below visualise this dynamic, plotting rolling and expanding window correlations between swaption-implied volatilities and inflation risk to highlight the pronounced strengthening of their comovement in recent times, while revealing contradictory evidence in the JPY market.

Figure 16. Rolling Window Correlations between Swaption-Implied Volatilities and Inflation Risk across Markets

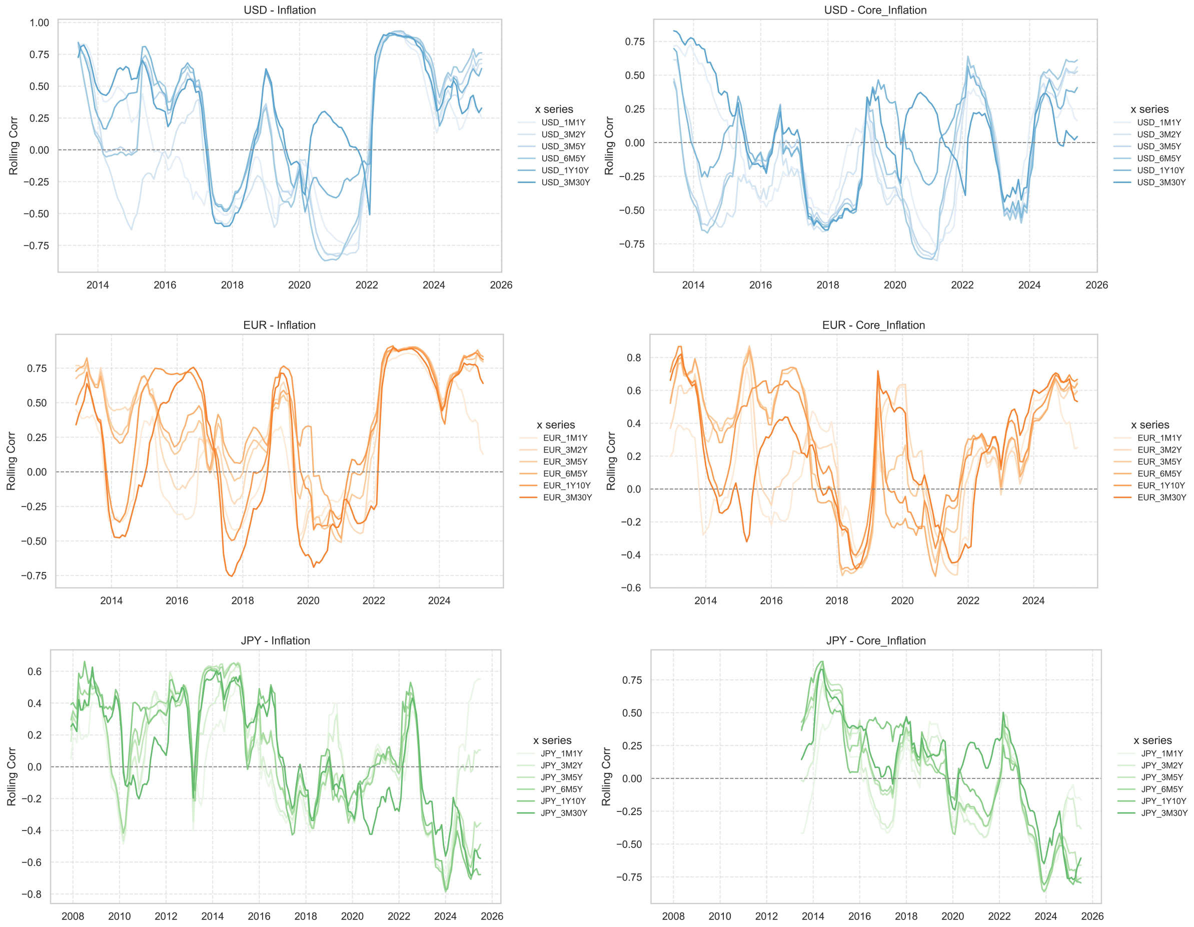
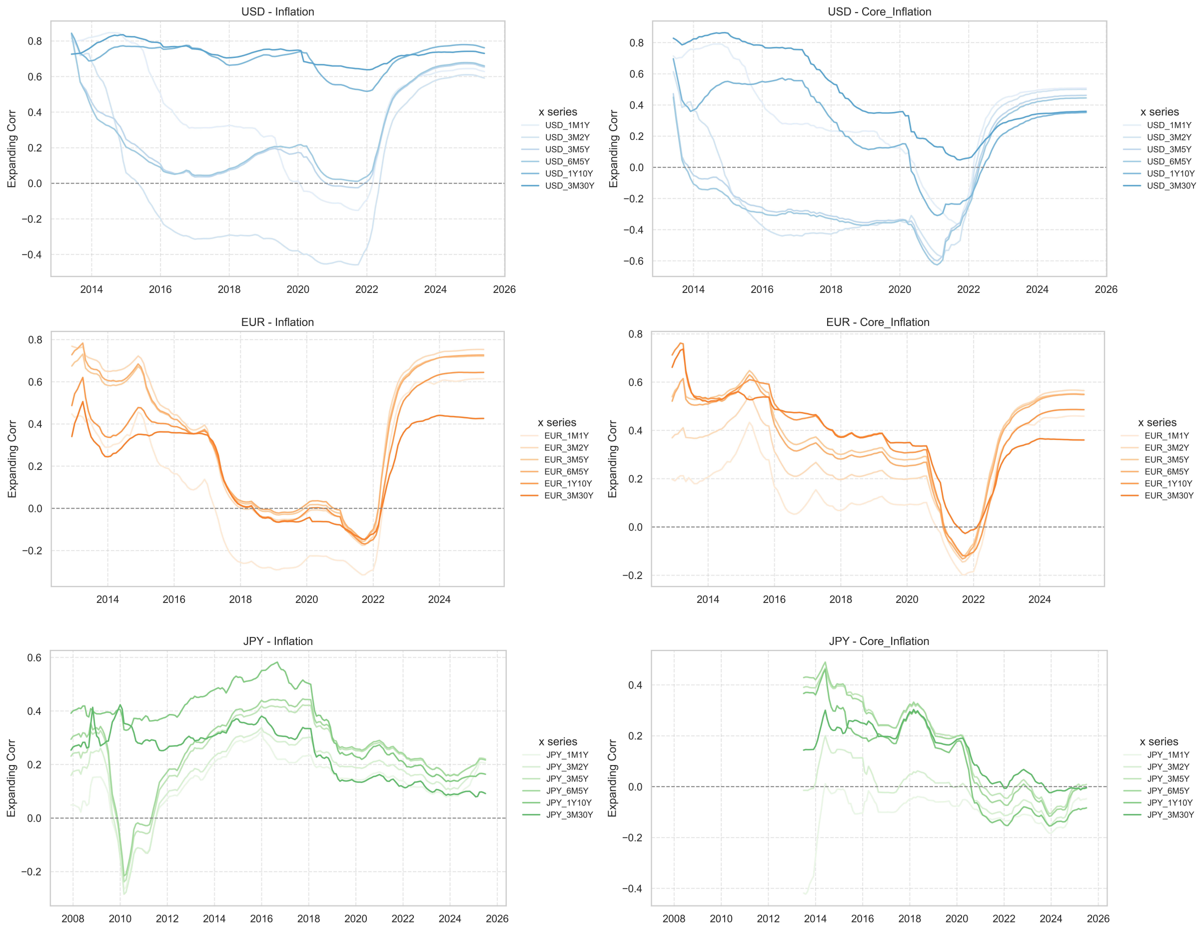


Figure 17. Expanding Window Correlations between Swaption-Implied Volatilities and Inflation Risk across Markets



5.3. Granger Causality Tests

The Granger causality tests largely confirm a strong feedback-type of relationship: macroeconomic volatility – especially in real-economy indicators such as inflation, industrial production, and unemployment – often anticipates movements in swap market volatility. Across specifications, reverse causality is statistically significant in the majority of cases, with p-values frequently below the 1% level in both directions. This pattern is not surprising as market prices adjust once shocks are revealed. But precisely because this strong reverse causality was expected, the real interest of this research lies in identifying cases where swap volatility clearly leads macroeconomic risk, embedding forward-looking expectations about uncertainty that have not yet appeared in the conventional indicators or indices.

The most convincing signals arise in the USD market, where short- to medium-tenor swaptions (e.g., 1M1Y, 3M2Y, 6M5Y) significantly Granger-cause the U.S. MPU index, with p-values well below 0.05 and robust NetGC scores. In the euro area, 2Y and 5Y swap volatilities anticipate inflation volatility at monthly horizons, while selected swap vols also show lead effects over FX risk, particularly EURUSD volatility. Crucially, the low-frequency component of swap volatility (LVOL), extracted via spline fitting, consistently delivers stronger and more stable predictive power than raw GARCH volatilities. Where raw GARCH measures often fail to rise above statistical noise, LVOL captures the persistent uncertainty dynamics that better align with future macroeconomic volatility. At the same time, swaption volatilities remain inherently forward-looking by construction, since they are priced on forward swap rates and therefore embed market expectations of future policy and rate risk. Taken together, these two perspectives provide complementary evidence that swap market volatility can carry genuine forward-looking information. The swap-macro risk pairs showing the highest NetGC score are considered top candidates to reveal stronger and more pure predictive contribution and together forms the basis for the regression analysis that follows.

In Appendix Tables 7, 8, and 9 rank the top candidates across volatility types and currencies bu NetGC scores, reporting number of selected lags and their joint statistical significance.

5.4. Predictive Models and Performance Evaluation

The final step of the analysis addresses the decisive question: can swap market volatility truly forecast macroeconomic uncertainty?

In-Sample

The in-sample regressions show that swap-based predictors deliver a clear improvement over autoregressive benchmarks once regime fixed effects (FE) are included. Across full-sample regressions, the autoregressive baseline explains on average over 70% of the variation in macroeconomic volatility; nonetheless the addition of swap volatility lags raises explanatory power further. The average incremental in R^2 of ARX models is around 2-3 percentage points, and in nearly 92% of cases the fit improves relative to the benchmark, with about a third of these gains statistically significant. Importantly, the type of predictor matters. The low-frequency component of swap rate volatility (LVOL) tends to provide larger improvements in raw explanatory power, while swaption implied volatility (IV) is more often statistically significant but episodic, suggesting that IV could be better at identifying sharp movements or turning points than at explaining the overall variance. “X-only” regressions confirm the necessity of controlling for persistence: while the predictor alone sometimes mechanically deliver high R^2, much of this reflects the strong inertia of macro volatility itself, hidden inside whatever right-hand-side (RHS) has been specified, rather than true predictive content.

Compressing multiple lags of the predictor into principal components provides a complementary view. PCA-ARX regressions perform broadly in line with ARX in terms of overall fit, with average R^2 levels almost identical. However, the increasing significance is revealing: for EUR LVOL, the first principal component, capturing the common level across lags, emerges as highly significant in two-thirds of cases, while in JPY LVOL it is the second principal component, the slope, that carries predictive content. In other words, in Europe, the slow-moving level of swap rate volatility dominates, while in Japan the steepness of the curve, the spread between short and long-term vol levels, appears more informative. The contrasting results for EUR and JPY may reflect differences in monetary policy regimes. In Europe, successive shifts in ECB policy, from quantitative easing (QE) to crises to recent rapid tightening, have produced substantial swings in swap volatility levels, making it the dominant signal. Conversely in Japan, decades of persistently low rates and control on curve steepness have compressed volatility levels, reducing their informational content. Under such a regime, rate spreads, i.e., the slope of the curves – both swap and yield curve – might become more informative about shifts in macro expectations.

IV predictors show lower and more variable significance in the PCA setup, still occasionally deliver strong signals.

Examining the results across different lags of X reveals how information is transmitted from the swap market. For LVOL, the first three lags are most important, with consistently positive coefficients that reflect the gradual risk transmission when referring to slow-moving trend. In contrast, swaption-implied volatilites display a more complex structure. The immediate lag is usually positive, but the subsequent two- to three-month lags often enter negatively, signaling fast mean-reverting corrections after volatility shocks. At longer horizons, IV regains significance with positive signs, suggesting that swaptions may embed longer-term expectations about macro risk. This layered lag profile is intuitive: derivative markets react quickly, correct over the short run, but also embed more profound information on future economic uncertainty.

Allowing coefficients to change across macroeconomic regimes demonstrates that the strength and even the sign of predictive relationships are time-dependent. LVOL coefficients are most powerful during early crisis, where positive significance rates exceed 27%, and remain solid in "normal" conditions. Their impact weakens considerably in the post Global Financial Crisis and QE phases, with significance shares dropping below 14%. The Covid pandemic brings mixed results for low-frequency swap vol with coefficients both positive and negative for different lags in the same regression. This instability suggests that the surge in uncertainty during the pandemic era is driven by external and unexpected shocks which leave little room for swap market volatility to provide a clean forward-looking signal.

Implied volatilities, by contrast, light up most strongly during early expansions, with over 70% of coefficients positive and significant, capturing the risk-on phases and the steepening of the volatility curve as economies emerge from downturns. They also retain some bite in the Covid regime, with about 20% of coefficients positive and significant, though again with unstable signs. Post 2008 and during monetary easing, IVs continue to provide occasional predictive signals, weakening during periods of acute stress and risk-off, when realized volatilities seem a better signal. This asymmetric behavior suggests that option-implied volatilities may not perfectly price risk across regimes. They tend to capture risk-on dynamics in positive moments of the cycle, when option prices are closer to genuine expectations; but during stress periods option premia and risk aversion dominate, making realized volatilities more informative. In this sense, IVs appear to reflect both expectations and state-dependent risk premia, consistent with evidence from the variance risk premium literature (Bollerslev, Tauchen, and Zhou 2009; Bekaert and Hoerova 2014).

The post 2022 period, marked by inflation shocks, geopolitical tensions and fast monetary tightening, further illustrates this cyclicality. In this regime, LVOL coefficients lose much of their predictive strength, with significance falling below 15%, and again with many mixed-sign cases. Similarly, swaptions-implied volatilities shows rare occasions of risk anticipation.

This weak predictive content during highly volatile periods gives support to the opposite interpretation of the swaps–macro association: rather than pricing in rare events ex ante, swap markets seem adjusting ex post, reacting sharply to headlines and data releases in times of high stress.

To complement the aggregate statistics, Tables 10 and 11 present detailed in-sample results for the strongest predictors across currencies and predictor classes. For each predictor–target pair, the tables report the median ARX beta coefficient, defined as the median of the estimated coefficients across all considered lags of the predictor, which provides a robust summary of its average effect on the target variable, tracing also the median beta evolution across regimes, highlighting how predictive relationships evolve over time. Incremental R^2 of ARX models over the autoregressive benchmark is also reported.

Table 10. Median Betas of LVOL Predictors – Full Sample and Regimes Evolution

The table reports, for each predictor–target pair, the gain in R^2 of an ARX model over an AR benchmark, and the median beta across the considered lags of the predictor over the full sample (β). Columns EE, ED, GFC, QE and ISU show the same median betas estimated separately within Early Expansion, Early Downturn, Global Financial Crisis, Post-GFC/Quantitative Easing, and Inflation Shock/Uncertainty regimes. COVID-19 coefficients are not reported due to the very short and unstable sample period.

Predictor (t)	λ	Target (t+1)	ARX vs AR	Full Sample β	β Across Regimes				
					EE	ED	GFC	QE	ISU
				USD					
10Y_LVOL	0,3	Ind Production	48,33%	-2,532	0,592	-0,056	1,347	-1,032	4,091
10Y_LVOL	0,3	Unemployment	36,69%	0,587	-0,438	0,816	-0,786	0	3,97
10Y_LVOL	0,2	MOVE	34,27%	0,537	0,338	1,335	-0,142	0,826	0,411
10Y_LVOL	0,2	EURUSD	22,96%	0,09	0,022	0,043	0,29	0,396	0,205
10Y_LVOL	0,2	VIX	22,03%	0,242	0,123	-0,331	0,194	0,439	-0,2
				EUR					
30Y_LVOL	0,25	EURJPY	19,37%	-0,374	-3,196	-13,269	0,763	-1,251	-2,438
30Y_LVOL	0,2	VIX	18,51%	0,445	2,869	0,746	0,521	0,348	-0,547
10Y_LVOL	0,1	EURUSD	17,30%	0,064	-0,841	0,181	0,356	0,031	-0,266
10Y_LVOL	0,1	MOVE	16,87%	0,234	1,034	0,022	0,618	0,333	0,298
30Y_LVOL	0,1	Unemployment	12,69%	-0,181	-0,096	0,309	-0,161	-0,128	-0,259
				JPY					
30Y_LVOL	0,2	Core Inflation	15,43%	-0,143	-	-	-	-0,18	-0,121
2Y_LVOL	0,3	MPU	10,60%	0,125	1,254	-	0,736	1,052	-0,002
30Y_LVOL	0	Confidence	9,57%	-0,104	0,193	-	0,011	0,021	-0,021
5Y_LVOL	0,6	GLOBAL EPU (CUR)	9,13%	-33,597	5,093	-	-6,384	16,87	-12,96
5Y_LVOL	0,6	GLOBAL EPU (PPP)	9,01%	-24,897	0,098	-	-1,129	20,621	-7,028

Table 11. Median Betas of Swaption IVs – Full Sample and Regimes Evolution

The table reports, for each swaption-implied volatility predictor and target variable, the gain in R2 of an ARX model over an AR benchmark, and the median beta across the considered lags of the predictor over the full sample (β). Columns QE and ISU show the same median betas estimated separately within the Post-GFC/Quantitative Easing and Inflation Shock/Uncertainty regimes. COVID-19 coefficients are not reported due to the short and unstable sample period.

Predictor (t)	Target (t+1)	ARX vs AR	Full Sample β	β Across Regimes	
				QE	ISU
		USD			
3M30Y	EURUSD	14,97%	-0,05	-0,055	-0,15
3M5Y	Inflation	9,00%	0,042	0,015	-0,075
3M2Y	Core Inflation	7,12%	-0,058	-0,003	-0,021
3M30Y	Ind Production	4,12%	0,307	-0,006	0,092
1M1Y	MPU	3,41%	0,048	0,122	-0,009
		EUR			
3M30Y	EURUSD	18,07%	-0,374	-0,015	-0,181
1Y10Y	EURUSD	15,12%	0,445	-0,251	-0,167
6M5Y	EURUSD	11,06%	0,064	-0,192	-0,061
3M5Y	EURUSD	10,96%	0,234	-0,132	-0,012
3M2Y	EURUSD	9,11%	-0,181	0,038	-0,004
		JPY			
3M2Y	USDJPY	8,02%	0,114	0,139	0,019
1M1Y	USDJPY	3,95%	0,186	0,2	-0,106
1Y10Y	USDJPY	2,14%	0,038	0,048	0,022
6M5Y	USDJPY	1,72%	0,165	0,168	-0,023

This layout highlights the edge of low-frequency over swaption-implied volatilities in in-sample explanatory power; however, this advantage may be inflated by its longer look-back window, in which the model can learn and might overfit the data.

These tables also show how all predictors are highly regime-dependent, which could translate into weaker out-of-sample performance since models are estimated with an expanding window.

Out-of-Sample

The decisive test of predictive power comes in the out-of-sample expanding window exercise. Here the picture becomes much more selective. Across nearly 120 forecast evaluations, only about half of the ARX models deliver positive incremental R_{OS}^2 relative to the autoregressive benchmark, the mean improvement is modest at around 0.5 percentage points and the significance of these gains falls well below the in-sample results, where roughly one-third were statistically significant. The in-sample evidence therefore confirms that swap-based predictors contain information beyond pure persistence, while suggesting that this explanatory power shifts with the economic cycle. Such instability helps explain why out-of-sample forecasting sets a much higher bar: the predictive content of swap volatility may be concentrated in particular regimes rather than uniformly present, and the expanding-window OOS evaluation does not account for regime separation, possibly deluting predictive gains that are specific to certain periods.

It is important to emphasize how demanding this benchmark is. The AR(1) model already captures the strong persistence of macroeconomic volatility, explaining most of its month-to-month variation. To put this in perspective, it is theoretically easier to forecast the next release of inflation or unemployment prints than to predict tomorrow's closing price of EURUSD. Macroeconomic indicators are inherently persistent and can therefore be explained to a large extent by their own past. Different story would be beating a constant historical mean: relative to such a naïve benchmark, predictive gains from swap-based variables would appear much larger (unlike in stock retruns predictions). Indeed, even simple autoregressive memory easily outperforms the mean, and adding swap-based predictors would further raise high R_{OS}^2. But this comparison is fragile, because it overstates predictability by ignoring persistence. Benchmarking against AR(1) is therefore both more conservative and appropriate for such persistent volatilities.

A further robustness check, previously mentioned, concerns how macroeconomic volatilities themselves are estimated. Both richer and more simple specifications have been tested out-of-sample. When richer GARCH specifications are used, the dependent variables become noisier, often overfitting short-run fluctuations. This inflates the variance of forecast errors and produces unstable OOS comparisons, with extreme positive and negative values. By contrast, when macro volatilities are estimated with parsimonious GARCH models, the targets are smoother and persistence is captured more cleanly. The result is that the distribution of OOS performance tightens: spurious extremes vanish, and the pockets of genuine predictability stand out more clearly, although also more moderately. In this stricter setting, the strongest results for MOVE remain intact and important additional signals also survive: MPU, EUR inflation volatility, and FX volatility continue to show modest but positive gains in prediction, while US industrial production and core inflation volatility benefit from occasional improvements from low frequency swap volatility signals.. This reinforces that the positive results are not artificial or distorsions of model over-complexity, but they persist under a leaner and more defensible definition of macroeconomic uncertainty.

It is important to note, however, that the apparent very strong "predictability" of MOVE index should not be interpreted as genuine forecasting of macroeconomic risk. MOVE itself is an option-implied index of US interest rate volatility, basically linked to the same underlying dynamics that moves the predictors.. Swap rate volatility, both implied and estimated, to forecast MOVE is therefore better understood as internal consistency within the rates-volatility complex: one measure anticipates another, rather than providing an independent signal about the macroeconomy. At the same time, this finding suggests that swap-based vol is more reactive than bond-based measures to genuine rate uncertainty.

At the same time, inflation, industrial production, and unemployment volatility — show little or no OOS improvement once persistence is controlled for. Gains that look sizable against a mean forecast mostly vanish when compared to AR(1). This reinforces the main conclusion: swap market volatility does incorporate useful information about macro uncertainty, as in-sample results demonstrate, but does not have relevant forecast capabilities.

Table 12 ranks the top five out-of-sample forecasting models for each currency, ranked by incremental R^2_{OS} of the ARX model relative to the benchmark. This highlights where swap-based predictors deliver innovative gains.

Table 12. Top 5 OOS forecasting models for each currency

The models are ranked by incremental R_{OS}^2 of ARX relative to the autoregressive AR(1) benchmark. The predictor column lists the swap-based volatility measure (LVOL for low-frequency swap volatility; IV for swaption-implied volatility), with the smoothing parameter λ shown for LVOL predictors. The target column reports the dependent variable being forecasted at 1-month horizon. "ARX lags" denotes the number of lags of the predictor used in the specification. The last two columns show the incremental forecasting performance of ARX and PCA-ARX models compared to the AR(1) benchmark. Clark-West Test significance is indicated by stars: * significant at the 10% level, ** at the 5% level, and *** at the 1% level and indicates whether the incremements are statistically signfiicance.

Predictor (t)	λ	**Target (t+1)**	**ARX lags**	**ARX vs AR**	**PCA-ARX vs AR**
USD					
5Y_LVOL	0,2	MOVE	4	15,91% ***	14,93% ***
3M5Y_IV	-	MOVE	2	5,04% ***	4,89% ***
3M2Y_IV	-	MPU	2	2,70% *	1,26% *
30Y_LVOL	0,25	Ind Production	4	1,66%	1,32%
3M30Y_IV	-	Inflation	4	1,42%	4,92% *
EUR					
2Y_LVOL	0,1	MOVE	4	10,62% ***	10,26% ***
3M2Y_IV	-	MOVE	2	4,80% **	1,42% *
30Y_LVOL	0,3	VIX	6	1,20% **	2,49% ***
30Y_LVOL	0,3	EURUSD	6	0,57%	-0,05% **
30Y_LVOL	0,1	Unemployment	4	0,33%	0,06%
JPY					
3M5Y_IV	-	USDJPY	6	2,92% ***	1,51% ***
2Y_LVOL	0,5	MOVE	6	3,08% ***	0,47% ***
30Y_LVOL	0	Confidence	3	2,67%	1,96%
10Y_LVOL	0,1	USDJPY	4	1,16% **	1,16% **
10Y_LVOL	0,6	GLOBAL EPU PPP	4	-1,24%	4,59% ***

Overall findings are consistent with the strong persistence of macroeconomic uncertainty. This helps explain why improvements over autoregressive benchmarks remain limited, in line with Ludvigson, Ma, and Ng (2021), who show that uncertainty itself is largely predictable from its own past. The overall stronger role of LVOL relative to IV in the results matches with Berger, Dew-Becker, and Giglio (2020), who argue that realized volatility shocks, rather than forward-looking measures, are the main drivers of macro fluctuations. Still, the sharper but more episodic signals from swaptions connect with Sarisoy's (2023; 2024), even if the predictive content results less persistent here. Strong correlation and reverse causality between swap volatility and macroeconomic uncertainty resumes earlier results of Azad and Fang (2011, 2012).

6. Conclusion

This thesis analyzed the multifaceted relationship between swap rate volatility and macroeconomic uncertainty, testing whether the former contains predictive information that can improve forecasts of the latter across USD, EUR and JPY markets. The study explored a dimension of this association that the existing literature has only hinted at but not investigated in depth.

Results confirm clear evidence of robust correlations: swap volatility moves closely with policy uncertainty indices, inflation and core inflation volatility, FX volatility, and option-implied measures such as VIX and MOVE. This demonstrates that swap markets do internalize and reflect expectations on future macro risk. Second, Granger causality analysis reveals strong evidence of reverse causality and feedback dynamics, often with directional asimmetries favoring macro-to-swaps transmissions. Rather than being a limitation, this underscores the tight and complex two-way interaction between financial markets and the real economy, making the extraction of clean predictive signals inherently challenging.

The forecasting performance is consistent with this complexity. In-sample regressions show that swap-based predictors do improve the perfomance of the autoregressive benchmark, with the slow-moving compoonent of swap GARCH volatiltiy capturing broad, longer-term risks, while swaptions-implied volatilities delivers sharper, more episodic signals, particularly around transitions in the cycle. Out-of-sample, however, predictive power largely fades against the conservative AR(1) benchmark – a far tougher test than the fragile historical average, which the predictors easily beat. This makes even modest incremental gains of 1–2% in OOS R squared innovative and meaningful, highlighting that swaps volatility is far from noise.

The broader contribution is clear: swap-based volatilities are not stable and consistent forecasters of macroeconomic uncertainty, but they are highly effective mirrors of it. Macroeconomic risk and rate derivatives markets interact continuously, influencing each other in a feedback loop. This complexity makes it difficult to extract clean predictive signals, but it also highlights the importance of considering one when analyzing the other – whether in policymaking, trading, or studying the macroeconomic environment.

Beyond its direct apport, this study might open space for further research. A central lesson from the analysis conducted is that results are heavily shaped by how macroeconomic uncertainty is measured. Future work could therefore focus on developing and testing alternative proxies for macro risk that align more closely with how uncertainty is perceived in real time. From a modeling perspective, more advanced approaches, such as stochastic volatility models, Bayesian methods, or enhanced GARCH frameworks (e.g., ASP-GARCH, DCC-GARCH), could refine volatility estimation and sharpen predictive tests.

Furthermore, whereas this study deliberately focused on a sinlge class of predictors – swap market volatilities – future research could extend the analysis to multivariate frameworks. In such a setting, machine learning optimization methods, such as random forests or neural networks, may be particularly valuable to capture nonlinear interactions and identify the most informative predictors when multiple X variables are considered simultaneously, improving forecasting accuracy.

Methodologically, the predictive framework could be extended in several ways. Quantile regressions, in the spirit of Sarisoy (2023), would clarify whether predictive content concentrates in the tails of macro distributions. Cross-market analyses could examine volatility spillovers across currencies, enhancing global understanding of the uncertainty transmission between real economy and financial markets. Swaption-implied volatility could also be decomposed into expected variance and the variance risk premium (Bollerslev, Tauchen and Zhou, 2009), distinguishing between genuine forward-looking information and priced in risk premia.

In this sense, this thesis should be seen as a first step in a broader research agenda on the role of swap markets in reflecting future macroeconomic uncertainty – providing not only new evidence, but also a foundation for future work to build on.

7. Appendix

Table 1. Data Description

The table reports the sample period, frequency, and data source for all series used in the analysis. When the sample size is reported separately by currency, the coverage differs across USD, EUR, and JPY. When a single range is shown without currency breakdown, the same sample coverage applies to all three currencies.

Series		**Sample Size**		**Frequency**	**Source**
Macroeconomic Indicators	USD	EUR	JPY		
CPI / HICP	1985–2025	1990–2025	1985–2025	Monthly	Datastream
Core CPI / HICP	1985–2025	1996–2025	2010–2025	Monthly	Datastream
Industrial Production	1985–2025	1991–2025	1993–2025	Monthly	Datastream
Unemployment Rate	1985–2025	1998–2025	1985–2025	Monthly	Datastream
Consumer Confidence	1985–2025	1985–2025	1985–2025	Monthly*	Datastream
Michigan Consumer Sentiment	1985–2025	-	-	Monthly	Datastream
Exchange Rates					
EURUSD		1985–2025		Daily	Bloomberg
USDJPY		1985–2025		Daily	Bloomberg
EURJPY		1986–2025		Daily	Bloomberg
News-based Policy Uncertainty Indices					
EPU	1985–2025		1987–2025	Monthly	Bloomberg
EPU Composite	1985–2025	1987–2025		Monthly	Bloomberg
MPU	1985–2025		1987–2025	Monthly	Bloomberg
Global EPU (Current Prices)	1997–2025			Monthly	Bloomberg
Global EPU (PPP adjusted)	1997–2025			Monthly	Bloomberg
Market-based Uncertainty Indices					
VIX		1990–2025		Daily	Bloomberg
MOVE		1988–2025		Daily	Bloomberg
Swap Rates					
2Y	1987–2025	1999–2025	1989–2025	Daily	Bloomberg
5Y	1987–2025	1999–2025	1989–2025	Daily	Bloomberg
10Y	1987–2025	1999–2025	1989–2025	Daily	Bloomberg
30Y	1997–2025	1999–2025	2003–2025	Daily	Bloomberg
Swaption-implied Volatilities					
1M1Y	2011–2025	2011–2025	2006–2025	Daily	Bloomberg
3M2Y	2011–2025	2011–2025	2006–2025	Daily	Bloomberg
3M5Y	2011–2025	2011–2025	2006–2025	Daily	Bloomberg
6M5Y	2011–2025	2011–2025	2006–2025	Daily	Bloomberg
3M30Y	2011–2025	2011–2025	2006–2025	Daily	Bloomberg
Recession Risk Indices					
Recession Probability Forecasts	2008–2025	2012–2025	2012–2025	Mixed**	Bloomberg
Real-time Sahm Rule Recession Indicator		1985–2025		Monthly	FRED
Smoothed U.S. Recession Probabilities		1985–2025		Monthly	FRED
GDP-Based Recession Indicator Index		1985–2025		Monthly	FRED
NY Fed Probability of Recession (Treasury Spread)		1985–2025		Monthly	Bloomberg
Fed U.S. Recession Probability Forecast Index		1985–2025		Monthly	Bloomberg
BBG Binary US Recession Index		1985–2025		Monthly	Bloomberg

*Japanese Consumer Confidence in quarterly frequency from 1985 to 2004 monthly afterwards.

**Monthly frequency until 2016, daily afterwards.

Figure 1. USD and JPY Swap Curves Comparison

The figure illustrates the evolution of alternative swap curves within the same market. For USD, IRS series from Datastream (historically based on LIBOR) are compared with SOFR-based curves; for JPY, Datastream IRS series (historically based on LIBOR) are compared with TONAR-based curves. These historical IRS series initially referenced LIBOR as the floating rate benchmark before transitioning to the respective alternative reference rates over time. The comparison shows that the evolution of the Datastream IRS series and the alternative benchmarks is virtually identical, supporting the use of the longer Datastream series for the empirical analysis.

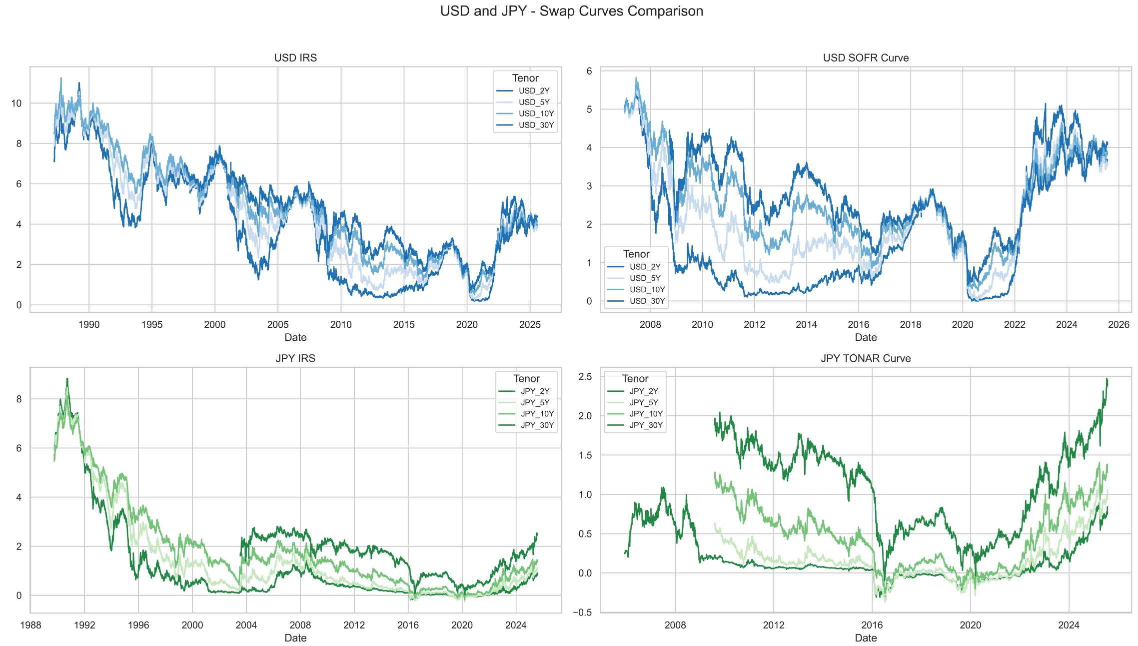


Table 2. ADF Test Results for Stationarity

This table reports Augmented Dickey–Fuller (ADF) test results for stationarity across financial and macroeconomic variables. Swap rates (2Y, 5Y, 10Y, 30Y) and exchange rates (EURUSD, USDJPY, EURJPY) refer to daily changes, while macroeconomic indicators (inflation, core inflation, industrial production, unemployment, consumer confidence, and consumer sentiment) are measured in monthly changes. Reported are test statistics, p-values, and significance levels for the three markets. The null of a unit root is strongly rejected in nearly all cases, confirming the series' stationarity.

Series	**T Statistic**			**P-value (%)**			**Stationarity**		
	USD	**EUR**	**JPY**	**USD**	**EUR**	**JPY**	**USD**	**EUR**	**JPY**
2Y SWAP	-13.13	-11.33	-11.78	0.00	0.00	0.00	***	***	***
5Y SWAP	-22.04	-14.54	-14.11	0.00	0.00	0.00	***	***	***
10Y SWAP	-17.09	-15.14	-28.72	0.00	0.00	0.00	***	***	***
30Y SWAP	-16.79	-37.50	-13.95	0.00	0.00	0.00	***	***	***
Inflation	-6.01	-6.40	-7.75	0.00	0.00	0.00	***	***	***
Core Inflation	-6.49	-4.13	-4.70	0.00	0.09	0.00	***	***	***
Ind. Production	-5.70	-15.02	-7.19	0.00	0.00	0.00	***	***	***
Unemployment	-12.80	-3.39	-4.03	0.00	1.12	0.13	***	**	***
C. Confidence	-16.79	-9.26	-4.67	0.00	0.00	0.01	***	***	***
C. Sentiment	-10.19	-	-	0.00	-	-	***	-	-
EURUSD		-44.16			0.00			***	
USDJPY		-26.62			0.00			***	
EURJPY		-24.69			0.00			***	

Table 3. Ljung-Box Test Results for Autocorrelation

This table reports Ljung–Box (LB) test results for autocorrelation across financial and macroeconomic variables. Swap rates (2Y, 5Y, 10Y, 30Y) and exchange rates (EURUSD, USDJPY, EURJPY) refer to daily changes, while macroeconomic indicators (inflation, core inflation, industrial production, unemployment, consumer confidence, and consumer sentiment) are measured in monthly changes. Reported are the Ljung–Box Q-statistics, p-values, and significance levels for the three markets. The null hypothesis of no autocorrelation is rejected in several cases, indicating the presence of serial correlation in the data.

Series	**Q Statistic**			**P-value (%)**			**Autocorrelation**		
	USD	**EUR**	**JPY**	**USD**	**EUR**	**JPY**	**USD**	**EUR**	**JPY**
2Y SWAP	36.92	55.65	101.70	0.01	0.00	0.00	***	***	***
5Y SWAP	25.81	25.65	82.26	0.40	0.42	0.00	***	***	***
10Y SWAP	22.36	21.67	75.72	1.34	1.69	0.00	**	**	***
30Y SWAP	39.27	-37.50	96.15	0.00	1.45	0.00	***	**	***
Inflation	92.85	102.63	27.62	0.00	0.00	0.21	***	***	***
Core Inflation	149.31	32.08	19.71	0.00	0.04	3.21	***	***	**
Ind. Production	44.31	24.97	12.72	0.00	0.54	23.99	***	***	No
Unemployment	12.48	369.20	23.59	25.43	0.00	0.88	No	***	***
C. Confidence	15.99	27.76	50.98	10.00	0.02	0.00	No	***	***
C. Sentiment	26.52	-	-	0.31	-	-	***	-	-
EURUSD		11.66			30.86			No	
USDJPY		18.67			4.46			**	
EURJPY		19.76			3.16			**	

Table 4. ARCH LM Test Results for Conditional Heteroskedasticity

This table reports ARCH Lagrange Multiplier (LM) test results for conditional heteroskedasticity across financial and macroeconomic variables. Swap rates (2Y, 5Y, 10Y, 30Y) and exchange rates (EURUSD, USDJPY, EURJPY) refer to daily changes, while macroeconomic indicators (inflation, core inflation, industrial production, unemployment, consumer confidence, and consumer sentiment) are measured in monthly changes. Reported are the ARCH LM statistics, p-values, and significance levels for the three markets. The null hypothesis of homoskedasticity is rejected in most cases, indicating the presence of ARCH effects in the data.

Series	LM Statistic			P-value (%)			Heteroskedasticity		
	USD	EUR	JPY	USD	EUR	JPY	USD	EUR	JPY
2Y SWAP	931.46	978.12	826.91	0.00	0.00	0.00	***	***	***
5Y SWAP	763.92	728.19	1002.71	0.00	0.00	0.00	***	***	***
10Y SWAP	573.92	693.13	720.71	0.00	0.00	0.00	***	***	***
30Y SWAP	1349.86	711.89	914.42	0.00	0.00	0.00	***	***	***
Inflation	46.51	32.11	2.59	0.00	0.00	85.80	***	***	No
Core Inflation	96.15	23.51	0.79	0.00	0.06	99.22	***	***	No
Ind. Production	18.95	138.58	18.98	0.43	0.00	0.42	***	***	***
Unemployment	1.54	120.74	28.74	95.65	0.00	0.00	No	***	***
C. Confidence	8.43	11.43	57.61	20.81	7.60	0.00	No	*	***
C. Sentiment	9.82	-	-	13.23	-	-	No	-	-
EURUSD		450.96			0.00			***	
USDJPY		398.13			0.00			***	
EURJPY		1004.36			0.00			***	

Table 5. Selected GARCH specifications for high-frequency financial series and fit diagnostic.

AR(k)–GARCH(p,q) denotes a model where the conditional mean follows an autoregressive process of order k, while the conditional variance is estimated using a GARCH model with p lags of past variance and q lags of past squared shocks. "Residual ARCH/AR" indicates that diagnostic tests detected mild remaining dependence in squared or raw residuals.

Vol Series	Model	Fit Diagnostic
EUR 2Y	AR(1) - GARCH(1,2)	Optimal Fit
EUR 5Y	AR(1) - GARCH(1,2)	Optimal Fit
EUR 10Y	AR(1) - GARCH(1,2)	Optimal Fit
EUR 30Y	AR(1) - GARCH(1,3)	Residual ARCH (long lags)
USD 2Y	AR(2) - GARCH(1,3)	Residual AR (long lags)
USD 5Y	AR(1) - GARCH(1,3)	Optimal Fit
USD 10Y	AR(1) - GARCH(1,2)	Residual ARCH (long lags)
USD 30Y	AR(1) - GARCH(1,3)	Residual AR (lag 1)
JPY 2Y	AR(1) - GARCH(1,2)	Optimal Fit
JPY 5Y	AR(1) - GARCH(1,2)	Residual AR (long lags)
JPY 10Y	AR(1) - GARCH(1,2)	Optimal Fit
JPY 30Y	AR(1) - GARCH(1,2)	Optimal Fit
EURUSD	GARCH(1,1)	Optimal Fit
EURJPY	AR(1) - GARCH(1,1)	Residual AR (lag 1 and 10)
USDJPY	AR(1) - GARCH(1,3)	Optimal Fit

Table 6. Selected GARCH specifications for macroeconomic series (where ARCH effects where detected) and fit diagnostic.

This table reports the final AR–GARCH specifications chosen for each macroeconomic volatility series. The notation AR(k1,k2,…) - GARCH(*p,q*) denotes a model where the conditional mean follows an autoregressive process of the given lags *k*, while the conditional variance is estimated using a GARCH model with *p* lags of past variances and q lags of past squared shocks. The GJR–GARCH(*p,o,q*) extension allows for asymmetric effects, where negative shocks may have a stronger impact on volatility than positive shocks.

The column "Dummies" indicates whether intervention dummies for the Global Financial Crisis (GFC) and/or COVID-19 pandemic were included in the mean equation. "Fit Diagnostic" summarizes the results of residual checks: "Residual ARCH/AR" signals that mild dependence remained in squared or raw residuals at certain lags, while "Optimal Fit" indicates that diagnostic tests did not detect remaining serial correlation or heteroskedasticity.

Vol Series	Model	Dummies	Fit Diagnostic
EUR Inflation	AR(1,12) - GARCH(1,1)	No	Resiudal AR and ARCH (long lags)
EUR Core Inflation	AR(1,12) - GARCH(1,1)	No	Resiudal AR and ARCH (mid lags)
EUR Industrial Production	AR(1,12) - GARCH(1,1)	Yes (GFC, Covid)	Residual AR (lag 5)
EUR Unemployment	AR(1,2,3,12) - GARCH(1,1)	Yes (GFC, Covid)	Optimal Fit
JPY Industrial Production	AR(1,12) - GARCH(1,1)	Yes (GFC, Covid)	Optimal Fit
JPY Unemployment	AR(1,12) - GARCH(1,1)	No	Residual AR (lag 10)
JPY Confidence	AR(1,12) - GARCH(1,1)	Yes (Covid)	Residual AR (lag 10)
USD Inflation	AR(1,12) - GARCH(1,1)	No	Residual AR (lags 1,5,10)
USD Core Inflation	AR(1,12) - GARCH(1,2)	No	Resiudal AR and ARCH (many lags)
USD Industrial Production	AR(1,12) - GJR-GARCH(1,1,2)	Yes (GFC, Covid)	Residual AR and ARCH (long lags)

Figure 7. Macro GARCH volatility with and without COVID-19

This figure compares full-sample GARCH volatilities with pre-COVID estimates (truncated at January 2020) for key macroeconomic indicators in USD, EUR, and JPY. The exercise highlights how the COVID-19 shock added an extraordinary volatility spike without altering the underlying pre-2020 dynamics.

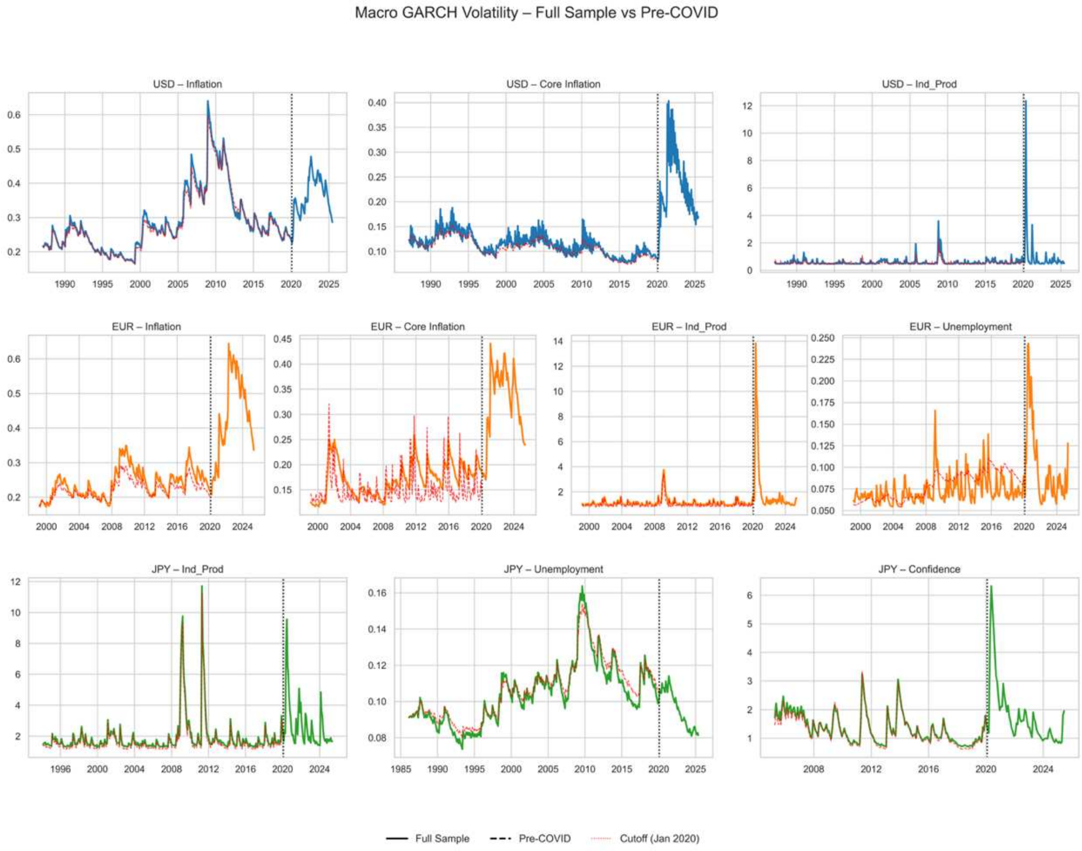


Figure 8. Swap Rate Volatility – Low Frequency Component for Alternative Smoothing Factors

This figure plots low-frequency volatility (LVOL) extracted from GARCH volatilities of swap rates for USD, EUR, and JPY across maturities. The solid line shows the original GARCH conditional volatility, while the red lines represent LVOL estimates obtained through spline smoothing with different parameters (λ ∈ [0, 0.1, 0.2, 0.25, 0.3, 0.4, 0.45, 0.5, 0.55, 0.6, 0.7]). Lower λ values (e.g., 0.1–0.2) track short-term fluctuations more closely, while higher values (e.g., 0.5–0.7) enforce smoother, low-frequency trends.

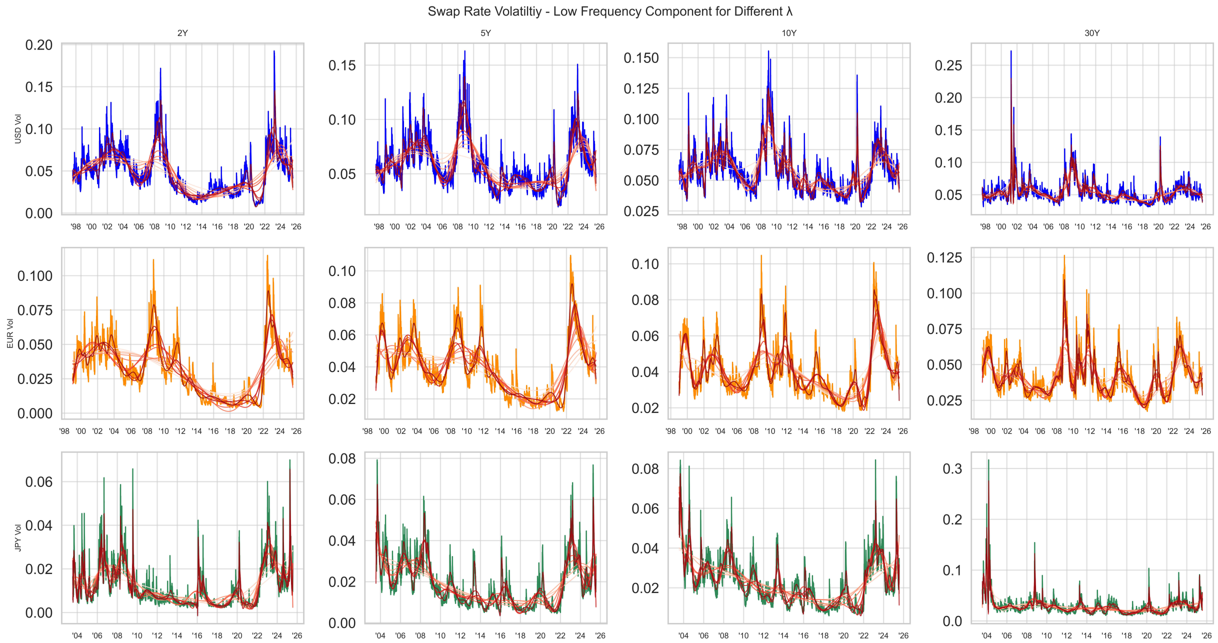


Figure 9. Swaption-Implied Volatilities

This figure plots implied volatilities from swaptions across USD, EUR, and JPY markets. These forward-looking measures capture market expectations of future swap rate uncertainty and provide the other main metrics to estimate swap market volatility.

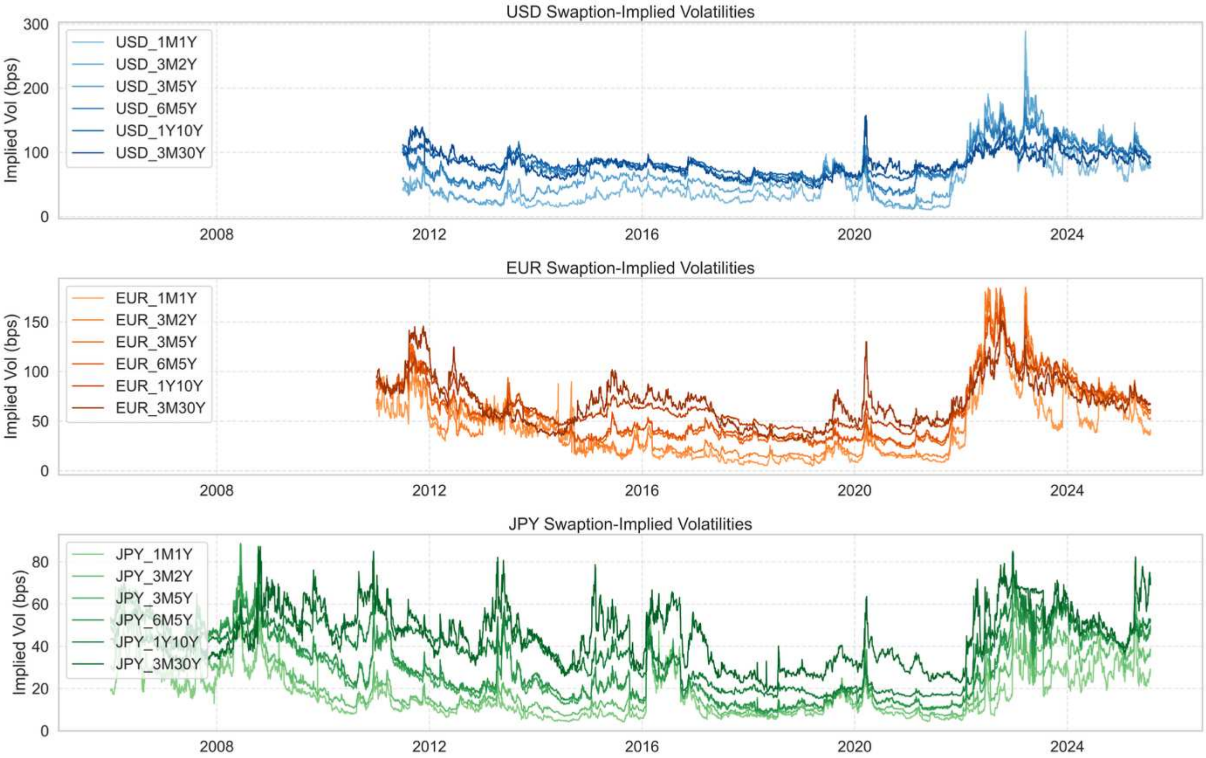


Figure 10. VIX and MOVE Indices

This figure shows the VIX equity volatility index and the MOVE bond market volatility index. Together, they summarize market-implied uncertainty in equity and Treasury markets, offering widely used benchmarks for financial stress and risk.

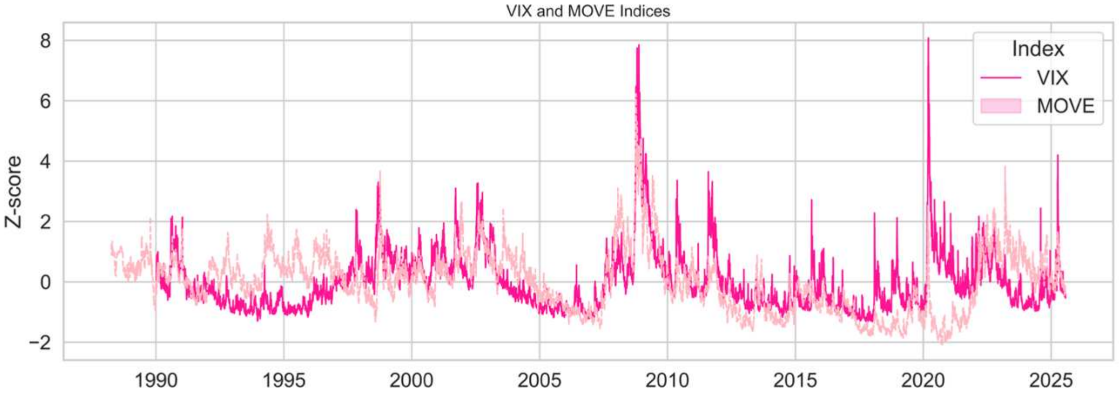


Figure 11. News-based Policy Uncertainty Indices

This figure plots the news-based indices of economic, monetary, and trade policy uncertainty for the United States, Euro Area, and Japan. These indices quantify policy-related uncertainty using the frequency of relevant terms in leading newspapers.

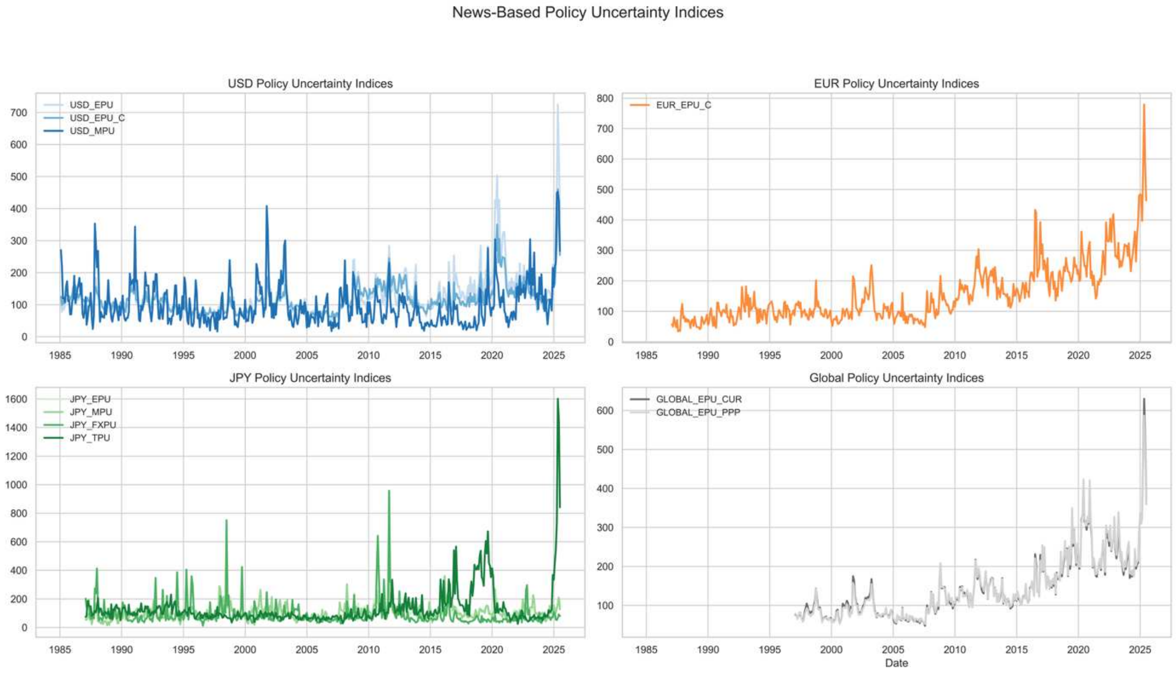
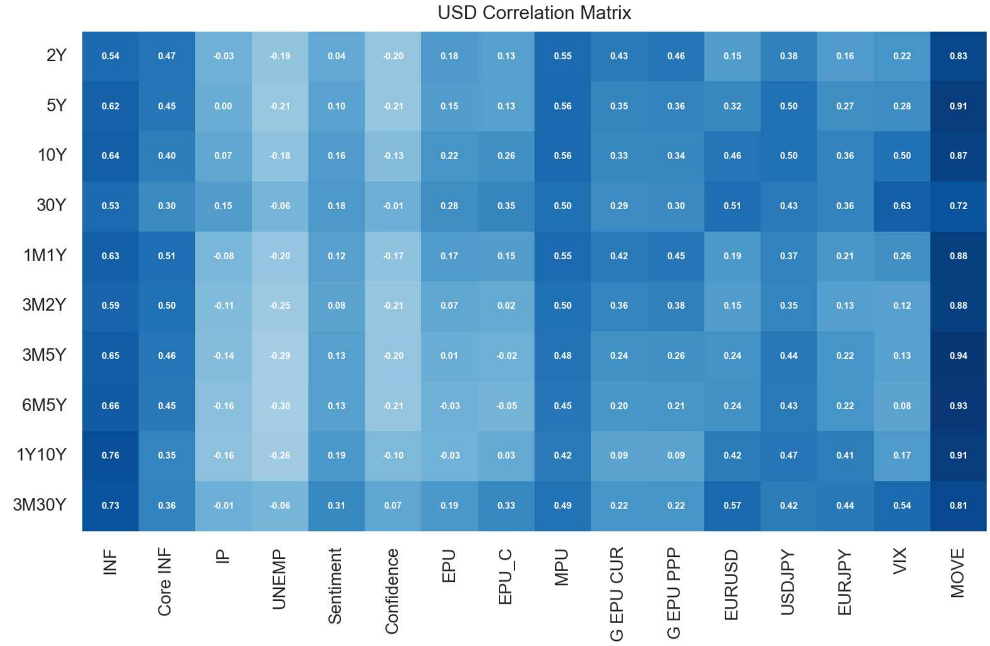


Figure 13. USD Correlation Matrix

Figure x. USD correlation matrix. The rows list swap-market volatilities by tenor — 2Y, 5Y, 10Y and 30Y (GARCH-estimated), and the swaption-implied volatilities for 1M1Y, 3M2Y, 3M5Y, 6M5Y, 1Y10Y and 3M30Y. The columns show macroeconomic and market indicators: Inflation (INF), Core Inflation (Core INF), Industrial Production (IP), Unemployment (UNEMP), Sentiment, Confidence, Economic Policy Uncertainty Index (EPU), Composite EPU (EPU_C), Monetary Policy Uncertainty Index (MPU), Global EPU indices (G EPU CUR and G EPU PPP), EURUSD, USDJPY and EURJPY volatilities, VIX, and MOVE.

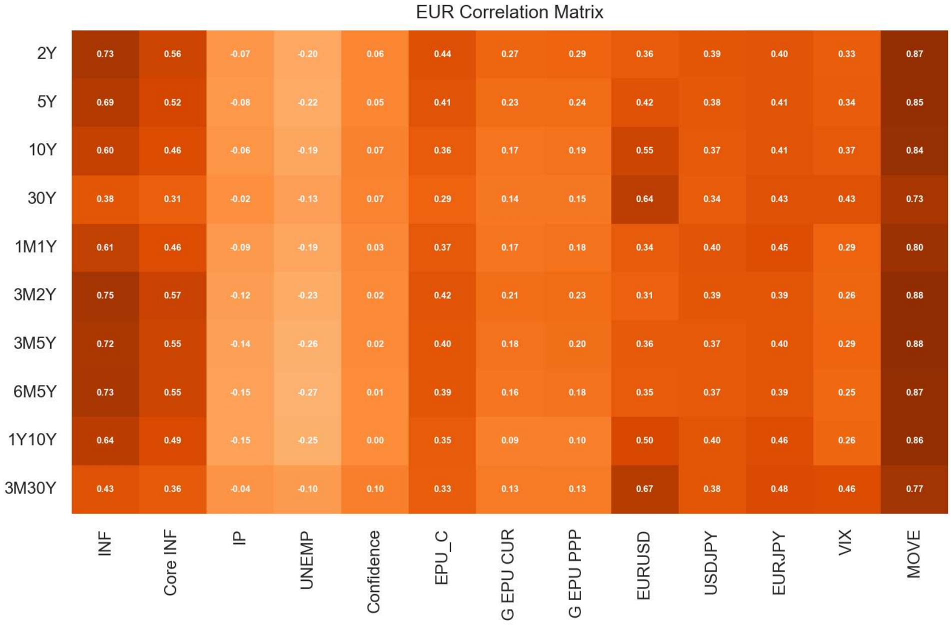


USD Correlation Matrix

	INF	Core INF	IP	UNEMP	Sentiment	Confidence	EPU	EPU_C	MPU	G EPU CUR	G EPU PPP	EURUSD	USDJPY	EURJPY	VIX	MOVE
2Y	0.54	0.47	-0.03	-0.19	0.04	-0.20	0.18	0.13	0.55	0.43	0.46	0.15	0.38	0.16	0.22	0.83
5Y	0.62	0.45	0.00	-0.21	0.10	-0.21	0.15	0.13	0.56	0.35	0.36	0.32	0.50	0.27	0.28	0.91
10Y	0.64	0.40	0.07	-0.18	0.16	-0.13	0.22	0.26	0.56	0.33	0.34	0.46	0.50	0.36	0.50	0.87
30Y	0.53	0.30	0.15	-0.06	0.18	-0.01	0.28	0.35	0.50	0.29	0.30	0.51	0.43	0.36	0.63	0.72
1M1Y	0.63	0.51	-0.08	-0.20	0.12	-0.17	0.17	0.15	0.55	0.42	0.45	0.19	0.37	0.21	0.26	0.88
3M2Y	0.59	0.50	-0.11	-0.25	0.08	-0.21	0.07	0.02	0.50	0.36	0.38	0.15	0.35	0.13	0.12	0.88
3M5Y	0.65	0.46	-0.14	-0.29	0.13	-0.20	0.01	-0.02	0.48	0.24	0.26	0.24	0.44	0.22	0.13	0.94
6M5Y	0.66	0.45	-0.16	-0.30	0.13	-0.21	-0.03	-0.05	0.45	0.20	0.21	0.24	0.43	0.22	0.08	0.93
1Y10Y	0.76	0.35	-0.16	-0.26	0.19	-0.10	-0.03	0.03	0.42	0.09	0.09	0.42	0.47	0.41	0.17	0.91
3M30Y	0.73	0.36	-0.01	-0.06	0.31	0.07	0.19	0.33	0.49	0.22	0.22	0.57	0.42	0.44	0.54	0.81

Figure 14. EUR Correlation Matrix

Figure x. EUR correlation matrix. The rows list swap-market volatilities by tenor — 2Y, 5Y, 10Y and 30Y (GARCH-estimated), and the swaption-implied volatilities for 1M1Y, 3M2Y, 3M5Y, 6M5Y, 1Y10Y and 3M30Y. The columns show macroeconomic and market indicators: Inflation (INF), Core Inflation (Core INF), Industrial Production (IP), Unemployment (UNEMP), Confidence, Composite EPU (EPU_C), Global EPU indices (G EPU CUR and G EPU PPP), EURUSD, USDJPY and EURJPY exchange-rate volatilities, VIX, and MOVE.



EUR Correlation Matrix

	INF	Core INF	IP	UNEMP	Confidence	EPU_C	G EPU CUR	G EPU PPP	EURUSD	USDJPY	EURJPY	VIX	MOVE
2Y	0.73	0.56	-0.07	-0.20	0.06	0.44	0.27	0.29	0.36	0.39	0.40	0.33	0.87
5Y	0.69	0.52	-0.08	-0.22	0.05	0.41	0.23	0.24	0.42	0.38	0.41	0.34	0.85
10Y	0.60	0.46	-0.06	-0.19	0.07	0.36	0.17	0.19	0.55	0.37	0.41	0.37	0.84
30Y	0.38	0.31	-0.02	-0.13	0.07	0.29	0.14	0.15	0.64	0.34	0.43	0.43	0.73
1M1Y	0.61	0.46	-0.09	-0.19	0.03	0.37	0.17	0.18	0.34	0.40	0.45	0.29	0.80
3M2Y	0.75	0.57	-0.12	-0.23	0.02	0.42	0.21	0.23	0.31	0.39	0.39	0.26	0.88
3M5Y	0.72	0.55	-0.14	-0.26	0.02	0.40	0.18	0.20	0.36	0.37	0.40	0.29	0.88
6M5Y	0.73	0.55	-0.15	-0.27	0.01	0.39	0.16	0.18	0.35	0.37	0.39	0.25	0.87
1Y10Y	0.64	0.49	-0.15	-0.25	0.00	0.35	0.09	0.10	0.50	0.40	0.46	0.26	0.86
3M30Y	0.43	0.36	-0.04	-0.10	0.10	0.33	0.13	0.13	0.67	0.38	0.48	0.46	0.77

Figure 15. JPY Correlation Matrix

Figure x. EUR correlation matrix. The rows list swap-market volatilities by tenor — 2Y, 5Y, 10Y and 30Y (GARCH-estimated), and the swaption-implied volatilities for 1M1Y, 3M2Y, 3M5Y, 6M5Y, 1Y10Y and 3M30Y. The columns show macroeconomic and market indicators: Inflation (INF), Core Inflation (Core INF), Industrial Production (IP), Unemployment (UNEMP), Confidence, Economic Policy Uncertainty Index (EPU), Monetary Policy Uncertainty Index (MPU), FX Policy Uncertainty Index (FXPU), Trade Policy Uncertainty Index (TPU), Global EPU indices (G EPU CUR and G EPU PPP), EURUSD, USDJPY and EURJPY exchange-rate volatilities, VIX, and MOVE.

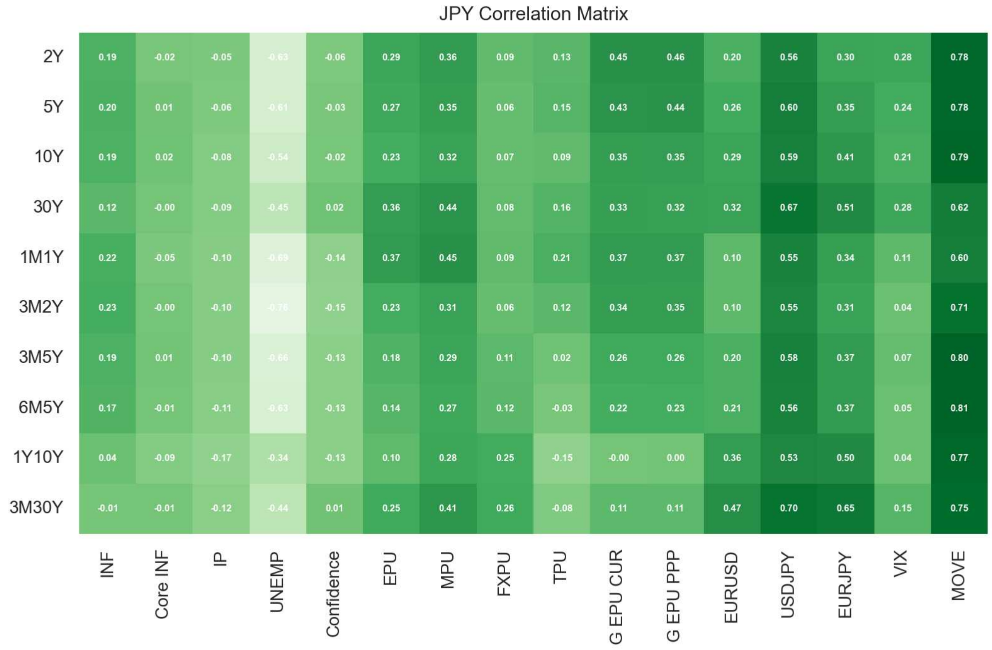


Table 7. USD – Top candidates for forecasting evaluation based on Granger causality tests

This table lists the predictor–target pairs with the strongest Granger-causality evidence in the USD sample. The upper panel reports swaption-implied volatilities at various maturities; the lower panel reports low-frequency swap-rate volatilities extracted with different smoothing factors (λ). For each pair the table shows the selected number of lags (BIC method), the Net Granger Causality (NetGC) score, the regression R², and statistical significance (*10 % level, ** at the 5 % level, and *** at the 1 % level) of the X overall contribution . These series represent the most promising predictors for subsequent out-of-sample forecasting exercises.

Predictor (t)	*λ*	Target (t+1)	BIC lags	NetGC	R2	Significance
		Swaption-Implied Vol				
3M30Y	-	Ind Production	3	30,357	52,56%	***
3M30Y	-	Unemployment	4	22,057	83,70%	***
3M30Y	-	EURUSD	2	7,680	82,96%	***
1Y10Y	-	EURUSD	2	6,996	82,91%	**
3M30Y	-	Core Inflation	3	5,278	92,64%	***
6M5Y	-	MOVE	1	5,184	83,20%	***
3M5Y	-	Core Inflation	3	4,582	92,80%	***
1M1Y	-	MPU	1	4,326	56,10%	***
3M2Y	-	MOVE	1	4,063	83,16%	***
6M5Y	-	EURUSD	2	3,833	82,70%	***
1Y10Y	-	USDJPY	1	3,382	60,41%	**
3M5Y	-	MOVE	1	3,258	83,07%	***
1M1Y	-	Inflation	1	3,045	93,40%	**
3M2Y	-	Inflation	1	2,972	93,30%	*
3M2Y	-	MPU	1	2,370	56,29%	***
6M5Y	-	USDJPY	1	2,248	60,30%	*

3M5Y	-	Inflation	1	2,130	93,30%	*
1Y10Y	-	Core Inflation	3	2,029	92,56%	***
3M5Y	-	EURUSD	2	1,775	82,52%	*
6M5Y	-	MPU	1	1,476	55,81%	***
1Y10Y	-	MPU	1	1,453	55,07%	***
6M5Y	-	Core Inflation	3	1,384	92,62%	***
3M5Y	-	USDJPY	1	1,324	60,22%	*
3M2Y	-	EURUSD	2	1,319	82,10%	***
3M5Y	-	MPU	1	0,669	55,78%	***
Low-Frequency Swap Rate Volatility						
10Y_LVOL	0,3	Ind Production	5	150,149	67,61%	***
10Y_LVOL	0,3	Unemployment	5	62,195	81,60%	***
10Y_LVOL	0,2	MOVE	6	59,585	87,82%	***
10Y_LVOL	0,25	MOVE	6	41,380	86,83%	***
2Y_LVOL	0,1	MOVE	5	40,933	86,12%	***
5Y_LVOL	0,2	MOVE	4	39,895	85,95%	***
5Y_LVOL	0,1	MOVE	6	37,717	86,19%	***
10Y_LVOL	0,2	Ind Production	6	34,725	48,60%	***
10Y_LVOL	0,2	VIX	6	33,185	77,01%	***
5Y_LVOL	0,25	MOVE	6	29,843	85,83%	***
10Y_LVOL	0,2	EURUSD	6	28,469	89,01%	***
10Y_LVOL	0,4	MOVE	6	27,045	85,52%	***
30Y_LVOL	0,25	Industrial_Prod	3	26,084	43,32%	***
10Y_LVOL	0,2	Unemployment	6	26,006	77,88%	***
10Y_LVOL	0,3	Core Inflation	5	25,750	92,57%	***
10Y_LVOL	0,3	MOVE	4	22,511	84,82%	***
10Y_LVOL	0,25	Ind Production	5	21,968	44,73%	***
5Y_LVOL	0,3	MOVE	6	21,598	85,12%	***
10Y_LVOL	0,2	USDJPY	6	20,569	73,47%	***
10Y_LVOL	0,45	MOVE	6	20,488	85,04%	***
5Y_LVOL	0,1	EURUSD	5	17,892	88,21%	***
10Y_LVOL	0,25	EURUSD	6	16,085	88,38%	***
30Y_LVOL	0,4	MPU	6	15,282	55,10%	***
10Y_LVOL	0,5	MOVE	5	15,184	84,06%	***
5Y_LVOL	0,4	MOVE	5	14,938	83,89%	***

Table 8. EUR – Top candidates for forecasting evaluation based on Granger causality tests

This table lists the predictor–target pairs with the strongest Granger-causality evidence in the EUR sample. The upper panel reports swaption-implied volatilities at various maturities; the lower panel reports low-frequency swap-rate volatilities extracted with different smoothing factors (λ). For each pair the table shows the selected number of lags (BIC method), the Net Granger Causality (NetGC) score, the regression R², and statistical significance (*10 % level, ** at the 5 % level, and *** at the 1 % level) of the X overall contribution . These series represent the most promising predictors for subsequent out-of-sample forecasting exercises.

Predictor (t)	*λ*	Target (t+1)	BIC lags	NetGC	R2	Significance
		Swaption-Implied Vol				
3M30Y	-	EURUSD	2	12,213	84,15%	***
1Y10Y	-	EURUSD	2	10,390	83,71%	***
3M2Y	-	MOVE	1	8,205	83,41%	***
6M5Y	-	EURUSD	2	6,432	83,14%	***
3M5Y	-	EURUSD	2	5,664	83,09%	***
6M5Y	-	MOVE	1	5,305	82,95%	***
3M5Y	-	MOVE	1	5,132	83,03%	***
3M2Y	-	EURUSD	2	3,611	82,74%	***
1M1Y	-	EURUSD	2	3,207	82,61%	**
1M1Y	-	MOVE	1	2,631	82,46%	**
1Y10Y	-	USDJPY	1	2,336	59,79%	**
6M5Y	-	USDJPY	1	1,805	59,53%	**
3M5Y	-	USDJPY	1	1,720	59,51%	**
		Low-Frequency Swap Rate Volatility				
30Y_LVOL	0,2	EURJPY	5	33,545	81,15%	***
2Y_LVOL	0,1	MOVE	4	25,865	86,01%	***
30Y_LVOL	0,2	VIX	5	22,063	75,81%	***
30Y_LVOL	0,2	EURUSD	5	21,432	88,99%	***
30Y_LVOL	0,25	EURUSD	4	19,481	88,85%	***
10Y_LVOL	0,1	MOVE	6	17,487	86,12%	***
2Y_LVOL	0,2	MOVE	6	17,463	85,92%	***
5Y_LVOL	0,1	MOVE	4	17,435	85,31%	***
30Y_LVOL	0,3	EURUSD	6	17,425	88,99%	***
30Y_LVOL	0,25	EURJPY	4	17,423	80,37%	***
30Y_LVOL	0,1	Unemployment	3	16,108	73,55%	***
10Y_LVOL	0,1	EURUSD	6	16,100	88,81%	***
30Y_LVOL	0,2	USDJPY	5	13,800	68,59%	***
30Y_LVOL	0,3	VIX	6	13,502	75,04%	***
5Y_LVOL	0,2	MOVE	6	11,662	85,44%	***
30Y_LVOL	0,3	EURJPY	6	11,521	79,07%	***
10Y_LVOL	0,1	VIX	5	10,923	73,80%	***
2Y_LVOL	0,25	MOVE	6	10,075	85,51%	***
2Y_LVOL	0,2	Inflation	6	9,981	95,84%	***
30Y_LVOL	0,1	USDJPY	3	9,441	66,74%	***
10Y_LVOL	0,2	VIX	5	9,346	73,09%	***
30Y_LVOL	0,25	USDJPY	4	8,524	67,61%	***
30Y_LVOL	0,55	MOVE	6	8,236	85,18%	***
5Y_LVOL	0,7	EUR EPU Comp.	6	8,122	83,36%	***
10Y_LVOL	0,1	EUR EPU Comp.	5	8,019	83,18%	***

Table 9. JPY – Top candidates for forecasting evaluation based on Granger causality tests

This table lists the predictor–target pairs with the strongest Granger-causality evidence in the JPY sample. The upper panel reports swaption-implied volatilities at various maturities; the lower panel reports low-frequency swap-rate volatilities extracted with different smoothing factors (λ). For each pair the table shows the selected number of lags (BIC method), the Net Granger Causality (NetGC) score, the regression R², and statistical significance (*10 % level, ** at the 5 % level, and *** at the 1 % level) of the X overall contribution . These series represent the most promising predictors for subsequent out-of-sample forecasting exercises.

Predictor (t)	**λ**	**Target (t+1)**	**BIC lags**	**NetGC**	**R2**	**Significance**
		Swaption-Implied Vol				
3M30Y	-	Confidence	2	5,190	78,25%	***
1M1Y	-	USDJPY	1	3,239	64,56%	**
1Y10Y	-	USDJPY	1	3,031	64,35%	**
1M1Y	-	Confidence	2	2,943	77,91%	**
6M5Y	-	USDJPY	1	2,809	64,69%	**
3M5Y	-	USDJPY	1	2,794	64,79%	***
3M2Y	-	USDJPY	1	2,310	64,66%	**
		Low-Frequency Swap Rate Volatility				
5Y_LVOL	0,6	TPU	6	13,757	76,61%	***
5Y_LVOL	0,7	TPU	6	13,757	76,61%	***
30Y_LVOL	0,1	Confidence	2	11,346	79,13%	***
30Y_LVOL	0	Confidence	2	10,999	79,07%	***
10Y_LVOL	0,7	TPU	4	10,014	74,94%	***
10Y_LVOL	0,6	TPU	4	9,970	74,76%	***
2Y_LVOL	0,7	TPU	5	8,242	75,75%	***
5Y_LVOL	0,6	GLOBAL EPU (CUR)	4	7,847	84,40%	***
5Y_LVOL	0,7	GLOBAL EPU (CUR)	4	7,847	84,40%	***
2Y_LVOL	0,2	TPU	3	7,740	74,80%	***
2Y_LVOL	0,1	Confidence	2	7,634	78,33%	***
10Y_LVOL	0,7	GLOBAL EPU (CUR)	4	7,450	84,30%	***
5Y_LVOL	0,6	GLOBAL EPU (PPP)	4	7,148	84,37%	***
5Y_LVOL	0,7	GLOBAL EPU (PPP)	4	7,148	84,37%	***
10Y_LVOL	0	Confidence	2	7,041	78,79%	***
10Y_LVOL	0,1	Confidence	3	7,008	78,75%	***
10Y_LVOL	0,7	GLOBAL EPU (PPP)	4	6,890	84,28%	***
10Y_LVOL	0,6	GLOBAL EPU (CUR)	4	6,605	84,21%	***
2Y_LVOL	0	Confidence	2	6,381	78,19%	***
2Y_LVOL	0,2	GLOBAL EPU (CUR)	3	5,855	82,94%	***
10Y_LVOL	0,6	GLOBAL EPU (PPP)	4	5,820	84,21%	***
30Y_LVOL	0,2	Core Inflation	5	5,632	66,30%	***
10Y_LVOL	0,2	USDJPY	5	5,628	67,46%	***
2Y_LVOL	0,5	MOVE	6	5,219	84,65%	***
5Y_LVOL	0,2	MPU	4	5,142	39,39%	***

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