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Simulating Tomorrow's Price: A Quantile-Based Approach to Forex Zones, USD/CHF Case

Yarının Fiyatının Simülasyonu: Döviz Bölgelerine Kantil Temelli Bir Yaklaşım, USD/CHF Örneği

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ABSTRACT

The main goal of the research is defined as designing an agile decision support framework for determination of optimal valuation intervals in the USD/CHF currency couple to optimize profit and cost. Therefore, the pricing ranges are tried to be defined by the utilizations of Quantile Regression Model with the integration of Monte Carlo simulations for testing the price actions for the next day. The computed intervals are respectively implemented for expected returns with risk-based approaches by the adoption of time series data from United States Central Bank's official website. Then as well, GARCH models are utilized to grab volatility swarming, and scenario simulations are processed to evaluate the risks and effectiveness of multiple trading formations. Consequently, an optimization engine based on grid search and evolutionary algorithms are occupied picked out to define varying formations that maximize expected utility while minimizing drawdown and transaction charges. As a result, these modeling approaches showed real time efficiency for catching the dyssymetric patterns over separate quantile regions, which provided by the combinations of Monte Carlo simulations with Garch-based volatility values that can improve the validity of derived price channels, particularly at chaotic market cases.

MAKALE BİLGİSİ

Makale Türü
Araştırma Makalesi

Anahtar Kelimeler
Kuantil Regresyon Analizi
Monte Carlo Simülasyonu
GARCH Modeli
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ÖZ

Çalışmanın amacı, USD/CHF döviz paritesinde kârı maksimize ederken maliyeti minimize etmeye yönelik optimal fiyat aralıklarının belirlenmesi için karar destek çerçevesi geliştirmektir. Geleneksel nokta-tahminine dayalı modellerden farklı olarak, önerilen yaklaşım aralık-temelli öngörü ve optimizasyona odaklanmaktadır. Bu doğrultuda öncelikli olarak, bir sonraki günün oynaklık bandını olasılıksal modelleme tekniği ile ön görebilmek için, volatilite harmonizasyonu ile bütünleştirilmiş Kuantil Regresyon ve Monte Carlo simülasyonları uygulanmıştır. Elde edilen bu aralıklar, beklenen getiriler ve birbirine bağlı riskler doğrultusunda dinamik olarak işlem açma, kâr alma ve zarar durdurma seviyelerini belirleyen bir kâr optimizasyon modeline girdi olarak hizmet etmektedir. Buna paralel olarak, volatilite kümelenmesini yakalayabilmek için GARCH modelleri kurulmuş ve çeşitli işlem senaryolarının performansını değerlendirmek amacıyla senaryo simülasyonları gerçekleştirilmiştir. Sonuç olarak, bu modelleme yaklaşımları, Monte Carlo simülasyonlarının Garch tabanlı oynaklık değerleriyle birleştirilmesiyle sağlanan ayrı kantil bölgeleri üzerindeki dissimetrik örüntülerin yakalanmasında gerçek zamanlı verimlilik sunarken, özellikle kaotik piyasa durumlarında türetilmiş fiyat kanallarının geçerliliğinin iyileştirilmesinde de kullanılabileceğini gösterdi.

1. Introduction

This study is developed to explore volatile nature of currency exchange markets by extracting a time series dataset from Fedeal Reserve Bank's data warehouse for USD/CHF instrument. Particularly, the analyses are made from a sample of 1.250 daily USD/CHF closing prices by the utilization of a stochastic simulation method which is formed on the geometric Brownian motion

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(GBM) model. For each day, the simulation of multiple future price paths is processed through incorporating random shocks derived from the historical volatility. From these simulations, the estimation of the 25th percentile (Q25) and 75th percentile (Q75) levels are calculated in terms of interpreting them as proxies for the lower (demand zone) and upper (supply zone) price boundaries, respectively. Therefore, analysts can get advantage of by using these zones which can be employed as probabilistic guidance on where price actions may occur to complement conventional chart-based assessments. In the existing literature, USD/CHF dynamics are rarely examined through a single-variable quantile regression based solely on lagged returns, leaving a clear gap. In this study, that gap is addressed by applying a simple, distribution-focused framework that reveals the tail behavior of USD/CHF.

The 25th–75th quantile range is selected because USD/CHF returns exhibit central clustering with mild asymmetry, making mean-based methods such as Ordinary Least Squares (OLS) insufficient for capturing distributional heterogeneity. The Quantile regression model is preferred to enable the prediction of tentative effects over disparate parts of the distribution, while an archetypical impact can be measured by just using OLS. Therefore, extreme tail behavior can be explored by centring on the interquartile band and informatory framework without clamor and unsteadiness in estimation capability in turbulent conditions.

The USD/CHF currency couple is selected because of its both heavily proven stabilized behavior and sensibility to macroeconomic variations, especially during the course of escalated ambiguity. The Swiss Franc (CHF) is universally determined esentially like a stability-based currency, that converts USD/CHF an explorative barometer for working on uneven market responses and asymmetric factors with quantile-based methods. Because of such these reasons, this asset class serves an exclusive domain in which the quantile regression structure can apprehend extraordinary-zone behavior more certainly relative to many alternative currency pairs.

However, it is reasonable to assume that choosing another currency such as USD/JPY, EUR/USD, or GBP/USD could yield different quantile structures due to differences in liquidity profiles, monetary policy regimes, and market microstructure characteristics. Therefore, the selection of USD/CHF inherently shapes the findings, particularly in the tail quantiles where market stress effects are more pronounced.

To address this concern and enhance the robustness of the study, a pseudo-design approach is proposed the research as well. A seperate simulation is also utilized by replicating the quantile-based forecasting procedure on a different historical window (e.g., the COVID-19 shock period). Such a robustness check would allow the evaluation of whether the quantile-zone dynamics observed in USD/CHF are structural features of the method or specific to the safe-haven characteristics of the Swiss Franc. Through this extension, the study is tried to be strengthened for the generalizability and empirical validity of the findings.

Particulary, in contemporary financial markets, definition of potential supply and demand zones is critical indicator for traders, risk managers, and analysts who have been searching to expect trend swings, price reversals or breakouts. Classical technical analysis regulary reckons on uniform historical levels or visually shown support-resistance fields, yet such approaches might bypass the dynamic character of price patterns under vagueness. Because of these mentioned reasons, this study offers a quantitative risk assessment framework to outline supply and demand zones by simulating next-day price distributions by utilizing statistical volatility in terms of extracting key quantile levels.

2. Literature Review

A novel observation-based model, the Generalized Autoregressive Conditional Beta, is proposed to capture time-impulsive gradients and beta spillovers in multi-dimensional heteroscedastic systems, with its analytical specifications incorporated and its reasonable relevance represented through practices to financial shock transmission (Grassi & Violante, 2025).

The identification and robust inference of return and volatility risk prices in asset pricing models with stochastic volatility are examined using a nonparametric exponentially affine framework, addressing the challenges posed by weak leverage effects and providing identification-robust confidence sets without relying on option data (Cheng, Renault, & Sangrey, 2025).

The investigations are performed to reveal how domestic financial uncertainties in stocks, bonds, and exchange rates, alongside global crises like the subprime mortgage and European debt crises, shape the dynamic correlation between the ASX 300 and major currencies using quantile regression on high-frequency data (1999–2021). By this way, currency-specific uncertainties and bond market volatility are evaluated through asymmetric effects on co-movements, with Australian bond market risk dampening correlations with the Euro and Pound as well as amplifying ties with the USD, Yen, and Yuan. While exchange rate volatility broadly enhances co-movements and global crises, particularly the subprime crisis, exert pronounced influence, offering key insights for portfolio and risk management (Irani, Al. Al. Hadood, Gokmenoglu, & Athari, 2025).

The explorations are performed for the fund flowing between green bonds and key financial markets utilizing quantile-on-quantile regression with daily data from 2008 to 2022. By unraveling lopsided and random interactions before COVID-19 and a strong negative correlation through the pandemic have been underscoring green bonds' potential like plating a role as a safe haven and risk diversification tool for traders, investors, and policymakers (Meo, Afshan, Ben Zaied, & Staniewski, 2025).

The examinations are utilized for whether ESG investments can serve as hedges or safe havens in the Indonesia Stock Exchange in the course of COVID-19. By taking the daily returns in line from ESG and traditional indices between 2017 and 2023; through the applications of GARCH and quantile regression approaches, the findings displayed ESG indices did not ensure hedge or safe haven compensations. So, investors should search for diversification in other asset alternatives such as metals, currencies, or bonds (Robiyanto, Agustina, Utami, Frensidy, & Huruta, 2025).

The clustering is performed in ASEAN-5 forex markets (Indonesia, Malaysia, Philippines, Singapore, Thailand) with the usage of daily data, cross-sectional absolute deviation (CSAD), and quantile regression. Findings showed that with no confirmation of herding behaviour, likely because of differetiation in economic fundamentals, and highlighting the significance of policy steadiness and risk diversifications (Danila & Aggarwal, 2025).

The exchange rate fluctuations are shown for exploring their effects in trade balances in G10 and BRICS countries with utilization of nonlinear quantile regression. That revealed advanced economies can illustrate short-run J-curve impacts, while emerging markets can be affected by pricing and quantity oscilations. Especially, bilateral exchange rates proposed much certain insights than effective rates, specifically for BRICS because of the US dollar's global role, which is highlighting significant policy implications like mitigation of the dollar dependence for BRICS and leveraging J-curve impacts in G10 policy structuring (Geldner, 2025).

The analyses are made for how African forex returns are influenced by oil prices (WTI) and geopolitical risk (GPR) using quantile-based causality, quantile regression (QR), and quantile-on-quantile regression (QQR) across 16 African currencies from 2000–2023. Findings illustrated that FX returns are asymmetrically and significantly shaped by oil and GPR, with directional causality from GPR and oil to FX. This condition caused to both positive and negative effects across quantiles, especially under extreme conditions, offering key insights for researchers, investors, and policymakers (Huang, Gubareva, Teplova, & Bossman, 2024).

The analyses are processed to show tail risk spillovers across G20 stock and FX markets, plus oil and gold, using a tail event network. The findings revealed that stocks drive most systemic risk, while assets like oil, gold, JPY, USD, and CNY can help to diversify it. On the other hand, quantile regression further showed asymmetric, market-specific spillover patterns, offering key insights for regulators and investors (Zixin, Jun, Zhang, & He, 2024).

The examinations are made to reveal how local realized exchange rate volatility and energy market implied volatilities (like OVX) affect BRICS currency returns using quantile regression (2012–2022). The results showed that OVX shocks negatively impact Russia's ruble across all quantiles, strongly affect India's and China's currencies in normal/booming markets, and influence South Africa and Brazil mainly in extreme market states. Notably, China shows sensitivity only at upper quantiles. The policy implications are also stated in terms of underlining the qualitative elements in macroeconomic environment (Qabhobho, 2023).

3. Research Design

3.1. Data Set

At first, the time series information set is taken out from Federal Reserve Economic Data for the time range which is defined between 4th April 2020 and 18th April 2025 into the Microsoft Excel program. After this operation, the set is arranged relative to the quantile regression modelling approach. While, the independent variables are defined as the previous day's returns, the dependent variables are defined as current day's returns.

3.2. Methodology

Later on, the quantile regression formula is performed for next steps with following structure;

$$y = a + bx \quad [1]$$

$$Q_\tau(y\backslash x) = a_{\tau +} b_\tau x \quad [2]$$

- $Q_\tau(y\backslash x)$: *The* τ^{th} *conditional quantile of* y.
- y is the predicted value of the dependent variable.
- x is the independent variable (predictor).
- a is the intercept (the value of y when x=0).
- b is the slope coefficient (the change in y for a one-unit change in x).

According to the sequence, two cells are derived in table in terms of stating the a which is representing the intercept value and the b which is representing the slope. Therefore, two new columns are added to the formation to express y (Predicted Y) as well as residuals (Errors) (Y-Predicted Y).

Table 1. Daily Quantile Regression Forecasting USD/CHF to Model Coefficients and Evaluation Metrics at τ = 0.05 for Framed Representative Time Scale

Date	USD/CHF	Lag1_Price	Lag1_Return	Y_NextClose	Predicted_Y	τ (tau)	0.05
20.04.2020	0.967	0	0	0.9691	0	a (intercept)	0.837689744
21.04.2020	0.9691	0.967	0.002171665	0.9711	0.837689744	b (slope)	0.00
22.04.2020	0.9711	0.9691	0.002063771	0.9731	0.837689744	Residual	Quantile_Loss (Pinball loss)
23.04.2020	0.9731	0.9711	0.00205952	0.975	0.837689744	-	-
24.04.2020	0.975	0.9731	0.001952523	0.9756	0.837689744	0.133410256	0.006670513
27.04.2020	0.9756	0.975	0.000615385	0.9743	0.837689744	0.135410256	0.006770513
28.04.2020	0.9743	0.9756	-0.001332513	0.9748	0.837689744	0.137310256	0.006865513
29.04.2020	0.9748	0.9743	0.000513189	0.9669	0.837689744	0.137910256	0.006895513
30.04.2020	0.9669	0.9748	-0.008104227	0.9599	0.837689744	0.136610256	0.006830513
1.05.2020	0.9599	0.9669	-0.007239632	0.9647	0.837689744	0.137110256	0.006855513
4.05.2020	0.9647	0.9599	0.005000521	0.9721	0.837689744	0.129210256	0.006460513
5.05.2020	0.9721	0.9647	0.007670778	0.9745	0.837689744	0.122210256	0.006110513
6.05.2020	0.9745	0.9721	0.002468882	0.9746	0.837689744	0.127010256	0.006350513
7.05.2020	0.9746	0.9745	0.000102617	0.9699	0.837689744	0.134410256	0.006720513
8.05.2020	0.9699	0.9746	-0.004822491	0.9722	0.837689744	0.136810256	0.006840513

$$\mathrm{Lag1}_{\mathrm{Price}}(t) = \mathrm{USD/CHF}_{(t-1)} \quad [3]$$

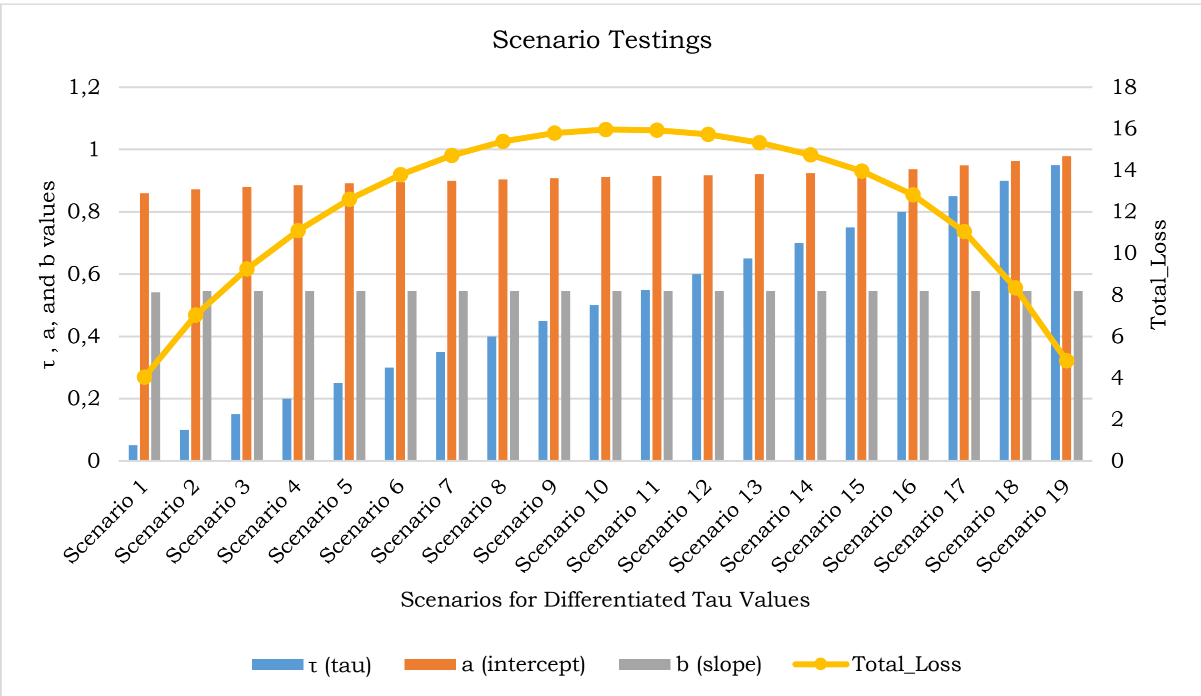
$$\mathrm{Lag1}_{\mathrm{Return}}(t) = (\mathrm{USD/CHF}_{(t)} - \mathrm{USD/CHF}_{(t-1)})/(\mathrm{USD/CHF}_{(t-1)}) \quad [4]$$

$$\hat{Y}(\mathrm{NextClose}) = \mathrm{USD/CHF}_{(t+1)} \quad [5]$$

$$\hat{Y}(\tau) = a_\tau + b_\tau X_\tau \quad [6]$$

As a result, the notations, which are mentioned above, are used to offer a risk framework for this financial instrument. After these operations, the quantile regression formula is enhanced with quantile loss function (pinball loss) by using the IF (Residual>= 0, τ * Residual, (1- τ) * ABS(Residual)) formulation to find total loss for each of the scenario which is iterated for every τ (tau) values. According to these results Excel Solver function is performed with GRG Nonlinear method to minimize total quantile loss by changing parameters which are referred to a and b values along with using any constraints because the objective of this research is not to restrict gradient (slope) direction. These different scenarios are tested and visualised to define probabilistic price range bands for the next steps of the research.

Figure 1. Scenario-Based Quantile Evaluation of τ, Intercept, Slope, and Total Loss



The visualization is made for how the quantile regression coefficients (intercept and slope) and the model's fit (total loss) change as the quantile (tau) varies. The intercept generally increases with tau, reflecting the increasing predicted price at higher percentiles. The slope remains positive, indicating a consistent positive relationship between the lagged return and the next day's price across the distribution, but the strength of this relationship (magnitude of the slope) varies. The total loss is highest around the central quantiles, suggesting that the linear model with only the lagged return as a predictor might have the most difficulty fitting the central part of the conditional distribution. The lower loss at the tails indicates a better fit for extreme price movements.

Table 2. Parameter Estimates and Forecast Loss Across Differentiated Quantile Scenarios (τ = 0.05 to 0.95)

Labels	τ (tau)	a (intercept)	b (slope)	Total_Loss
Scenario 1	0.05	0.8597063	0.5413939	4.0453088
Scenario 2	0.1	0.8722187	0.5460803	7.0263798
Scenario 3	0.15	0.8796647	0.5460827	9.2465475
Scenario 4	0.2	0.8856702	0.5460847	11.08653276
Scenario 5	0.25	0.8912056	0.5460862	12.60715371
Scenario 6	0.3	0.8958553	0.5460855	13.78655214
Scenario 7	0.35	0.8997953	0.5460856	14.71748924
Scenario 8	0.4	0.9039578	0.546086	15.3875728
Scenario 9	0.45	0.9080014	0.5460864	15.79067416
Scenario 10	0.5	0.9116189	0.5460863	15.96495416
Scenario 11	0.55	0,9147581	0.5460859	15.93548267
Scenario 12	0.6	0.9176079	0.5460851	15.72555419
Scenario 13	0.65	0.9207736	0.5460848	15.33551102
Scenario 14	0.7	0.9240600	0.5460846	14.74392898
Scenario 15	0.75	0.9284981	0.5460836	13.95481973
Scenario 16	0.8	0.9361378	0.5460822	12.8229454
Scenario 17	0.85	0.9486291	0.5460819	11.04747445
Scenario 18	0.9	0.9634923	0.546081	8.33223607
Scenario 19	0.95	0.9792096	0.5460819	4.825024939

Label descriptions are made for the values in this table like following order;

• τ (tau) is representing a value between 0 and 1 for the quantile levels (e.g., 0.05 = 5th percentile, 0.5 = median, 0.95 = 95th).

• a_τ is holding the intercept of the quantile regression line for that τ.

• b_τ is capturing the slope coefficient which is showing the effect of input (e.g., Lag1_Return).

• Total_Loss is carrying the loss function (pinball loss) which is used to assess fit quality at each τ level.

According to this table, most b (slope) values are consistent with the varying τ values which is indicating stable effect of Lag_1Return as well as a (intercept) values increase with τ values which is expected since higher quantiles are enable to estimate higher price levels.

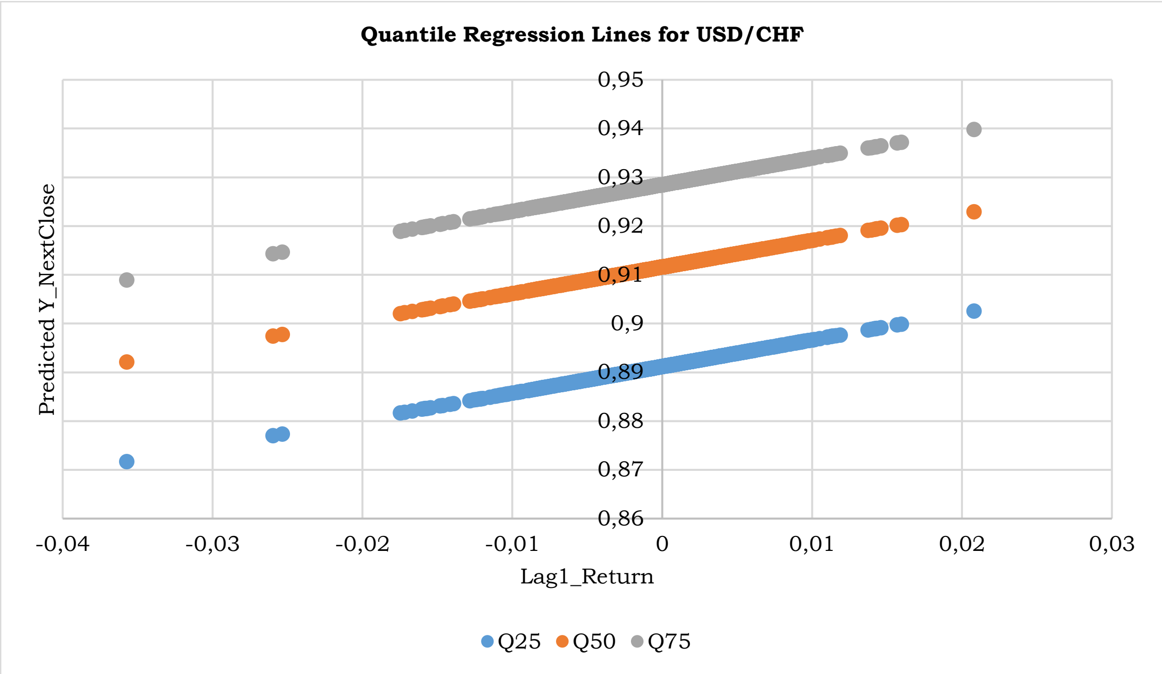
Table 3. Quantile-Based Predicted USD/CHF Prices According to Lagged Returns

Lag1_Return	τ = 0.25	τ = 0.5	τ = 0.75	Q25	Q50	Q75
0	0.891206	0.911619	0.928498	0.891206	0.911619	0.928498
0.002171665	0.546086	0.546086	0.546084	0.892392	0.912805	0.929684
0.002063771				0.892333	0.912746	0.929625
0.00205952				0.89233	0.912744	0.929623
0.001952523				0.892272	0.912685	0.929564
0.000615385				0.891542	0.911955	0.928834
-0.001332513				0.890478	0.910891	0.92777
0.000513189				0.891486	0.911899	0.928778
-0.008104227				0.88678	0.907193	0.924072

This table is designed to define the three quantiles which are determined as 0.25, 0.5, and 0.75. Each of the cells, which are belonging to the predefined quantile ranges like in the table, are computed by using the formulations shown above. After analyzing this table, the plot of quantile regression lines is formed such below.

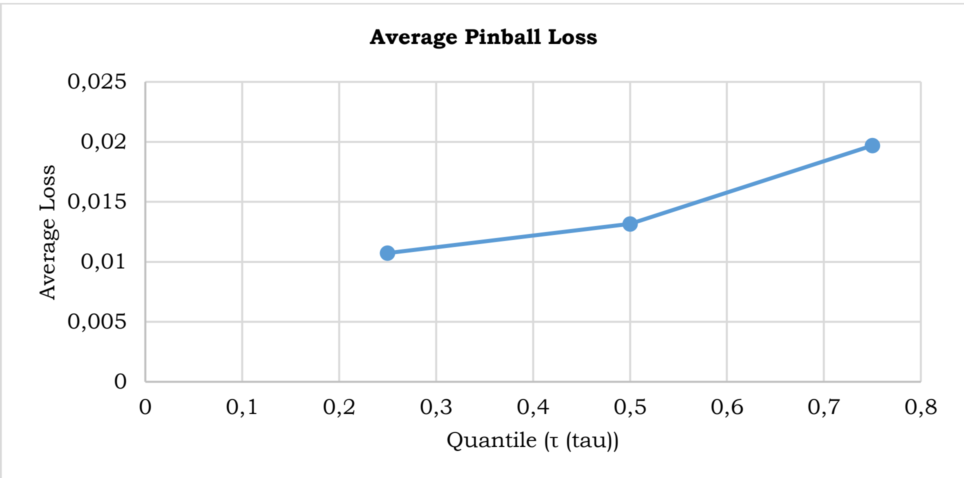
Quantile regression does not deliver conventional p-values because the estimator is non-parametric and its sampling for distribution is asymmetric (Koenker & Bassett, Regression Quantiles) 9. According to this reason, estimated coefficients, bootstrap standard errrors, and corresponding quantile levels (Q25, Q50, Q75) are demonstrated to represent statistical rigor of the analyses.

Figure 2. Quantile Regression Lines for USD/CHF Based on Lagged Returns



To assess the heterogeneous effects of lagged returns on future price movements, a quantile regression model is employed. Specifically, examination is made for how the previous day's return (Lag1_Return) influences the predicted next day's closing price (Predicted Y_NextClose) across the 25th (Q25), 50th (Q50), and 75th (Q75) percentiles.

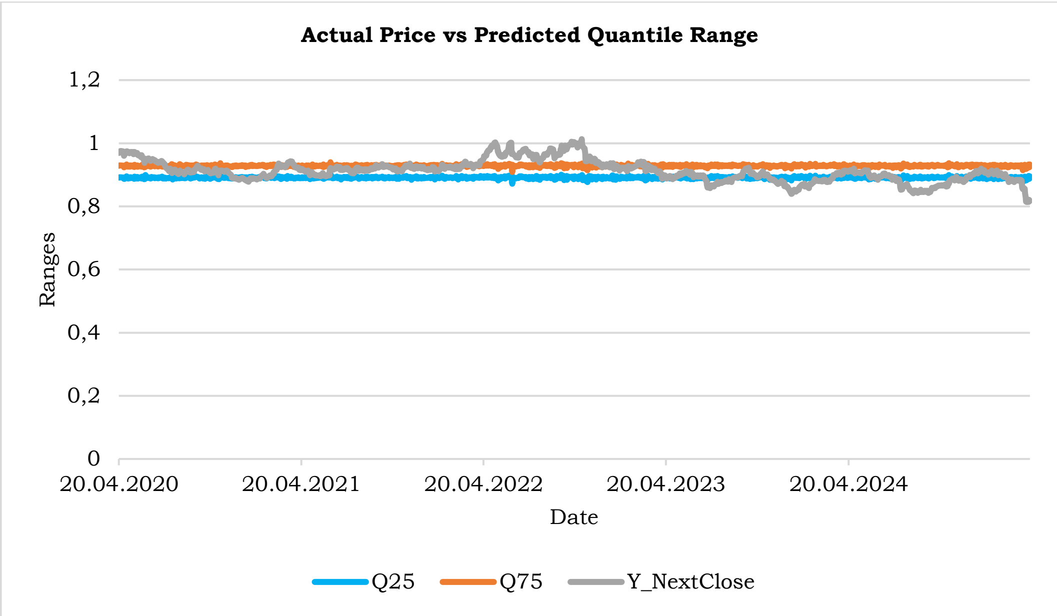
Figure 3. Average Pinball Loss Across Selected Quantiles (τ)



3.2.1. Analyzing the Trend

The volatility indicator which is shown as average pinball loss provides that which zones are critical while taking decisions to buy, wait, or sell actions. In this case, the asymmetric nature of the market condtions are displayed with where underprdictions can be much costly at lower quantile levels or overpredictions are such similarly much costly at higher quantile levels.

Figure 4. Range Bound Levels



3.2.2. Model Development

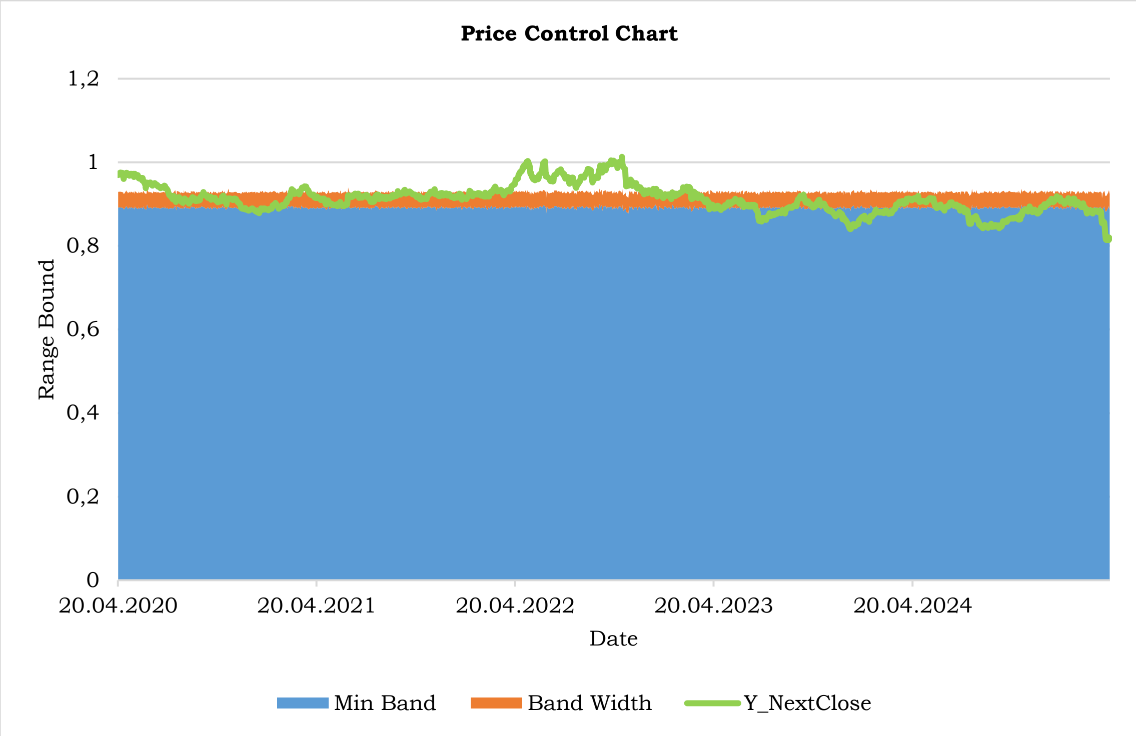
First of all predicted range is observed. The area between the blue line (Q25) and the orange line (Q75) can be interpreted as the predicted interquartile range (IQR) of the USD/CHF price based on the model. This range represents where the middle 50% of the predicted price distribution is expected to lie. Secondarily, actual price action and trajectory are explored. The green line (Y_NextClose) shows the actual fluctuation of the USD/CHF price over the observed period.

The actual price (green line) generally stays within or near the predicted interquartile range (between the blue and orange lines) for a significant portion of the time. This suggests that the quantile regression model is enable to capture the central tendency and typical price volatility reasonably efficiently.

However, there are still periods where the actual price moves outward of this simulated IQR. This reveals that the actual price encountered further extreme wavings than what the model displayed for the centric 50% of the distribution. For example, there are extraordinary price actions above the Q75 line and below the Q25 line at numerous points.

Volatility is searched within the interval between the Q25 (blue) and Q75 (orange) lines specifies a visual implication of the simulated volatility or scatter of the central 50% of the price distribution relative to the model. The breadth of this band comes across to change somewhat over period of time, prescribing that the model envisages periods of higher and lower instability.

Figure 5. Price Band Analysis with Next Close Prediction



3.3. Findings

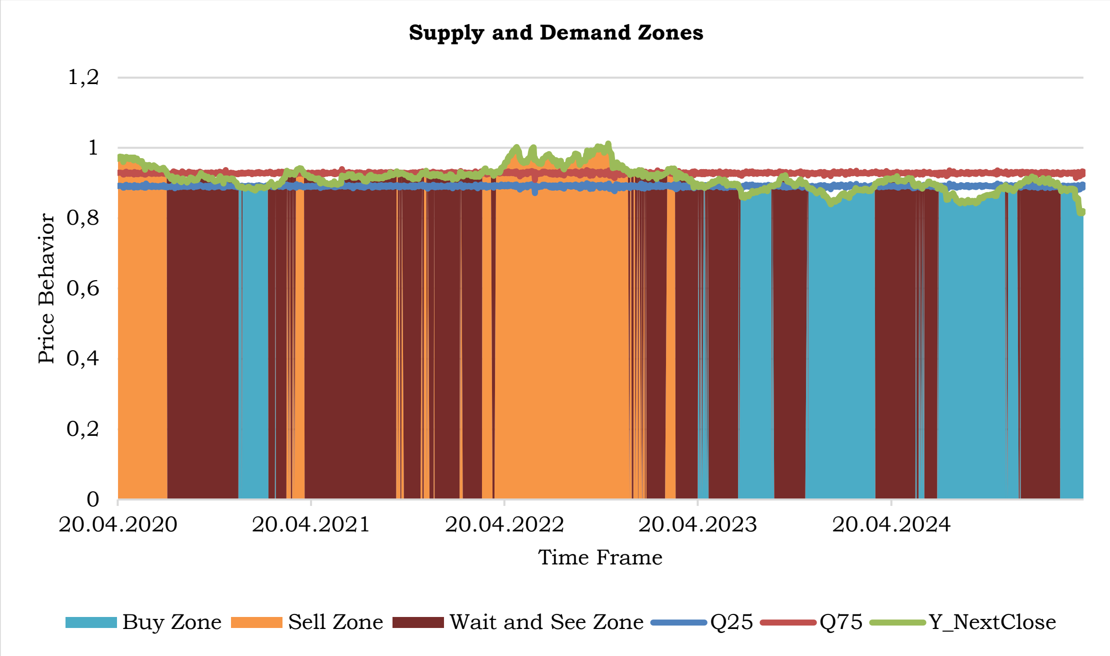
Quantile regression model is tested by this chart to clarify plausible price intervals with simulated control band which is nearly equivalent to the interquantile range that stays relatively consistent across time in terms of offering a benchmark for what can be assessed as normal price behavior. According to this sample, the market price follows the expected corridor, supporting the capability of model for tracking the central Dynamics of the fluctuating exchange rates.

Model Performance is tested with following implications:

- The reality that the factual price often remains within the predicted IQR offers that the model has a proportion of predictive power for the central tendency of the price acts.
- The occasions where the actual price moves away the IQR indicate the limitations of the model in capturing exceptional price pivots and swings. This is anticipated, since the IQR uniquely contains the middle 50% of the distribution.

A consistent positive interrelation is defined between the return of a day before and the next day's price tendencies which proves that the momentum of short term can carry the trend forward for the following session. Also, by using this way the differentiation between quantile zones can be defined clearly versus conventional mean-focused predictors, as also it can capture distributional ranges that may else remain hidden.

Figure 6. Supply and Demand Zones with Actual Price and Predicted Quantile Ranges



3.4. Discussions

Dynamic buy, sell, and neutral fields are visualized to offer a much more feasible decision-making tool through the classification of time zones with price harmony. Particularly, by using the estimated 25th and 75th percentile price band widths like a statistical guidance, the chart exhibits time frames where the exchange rate can considered as undervalued, overextended, or simply moving within a stable typical range. When the actual price changes relative to these model-based fields, the associated zone shifts for supporting the identification of timings when upward or downward actions are more probable, while also flagging time frames where taking a position would be less justified. For much of the time series, the signals synchronize intuitively with price tendency, illustrating rebounds after buy signals and pullbacks following sell behaviour, although sharp special market shocks can concisely reduce their reliability. As a result, this stratified representation empowers the interoperatability of the model by connecting statistical techniques with actionable trading insights, making the outputs much practical to employ in strategic risk assessments and short-term market decisions.

Future extensions of this framework may cover:

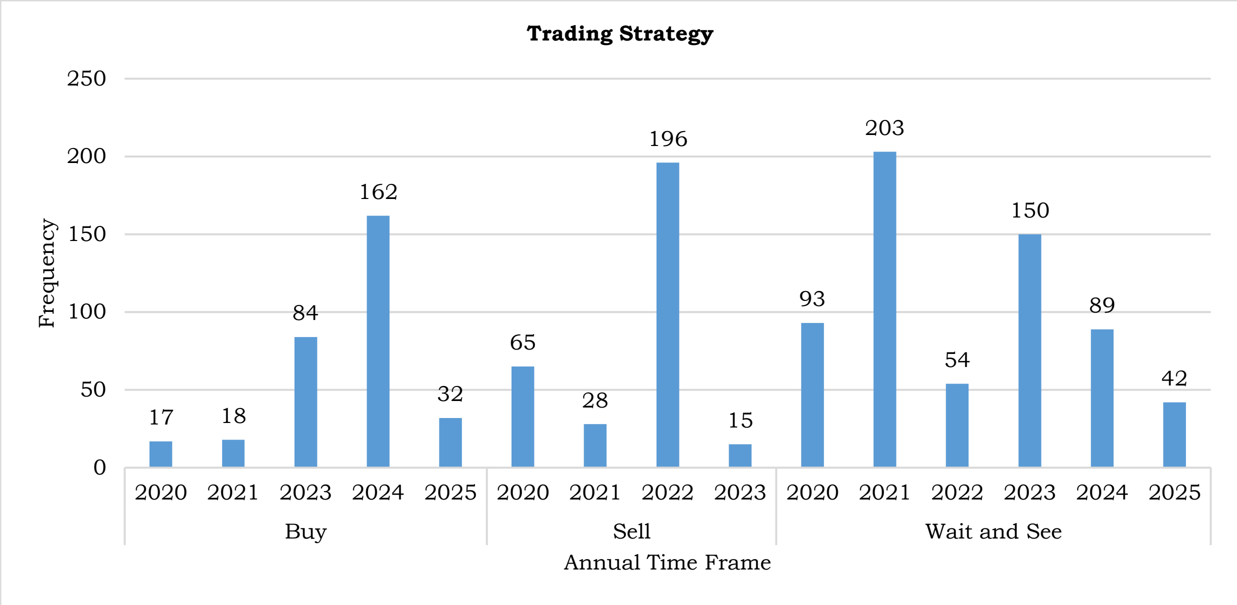
• Incorporation of probabilistic thresholds or volatility-adjusted bands to make zone transitions more robust.

• Machine learning classifiers to dynamically assign zones based on lagged features and latent state changes.

• Backtesting the effectiveness of each zone on out-of-sample price data to establish performance benchmarks and error bounds.

In summary, this "Supply and Demand Zones" chart provides a visual configuration for feasibly supporting trading decisions on USD/CHF, that is integrating price action, predicted quantile ranges, and structured trading zones. However, an in-depth evaluation is also required to comprehend the methodology behind the zone determination and a quantitative assessment of their statistical performance. Because of this reason, background of the currency's price action is analyzed through a bar chart to perceive trend behaviour.

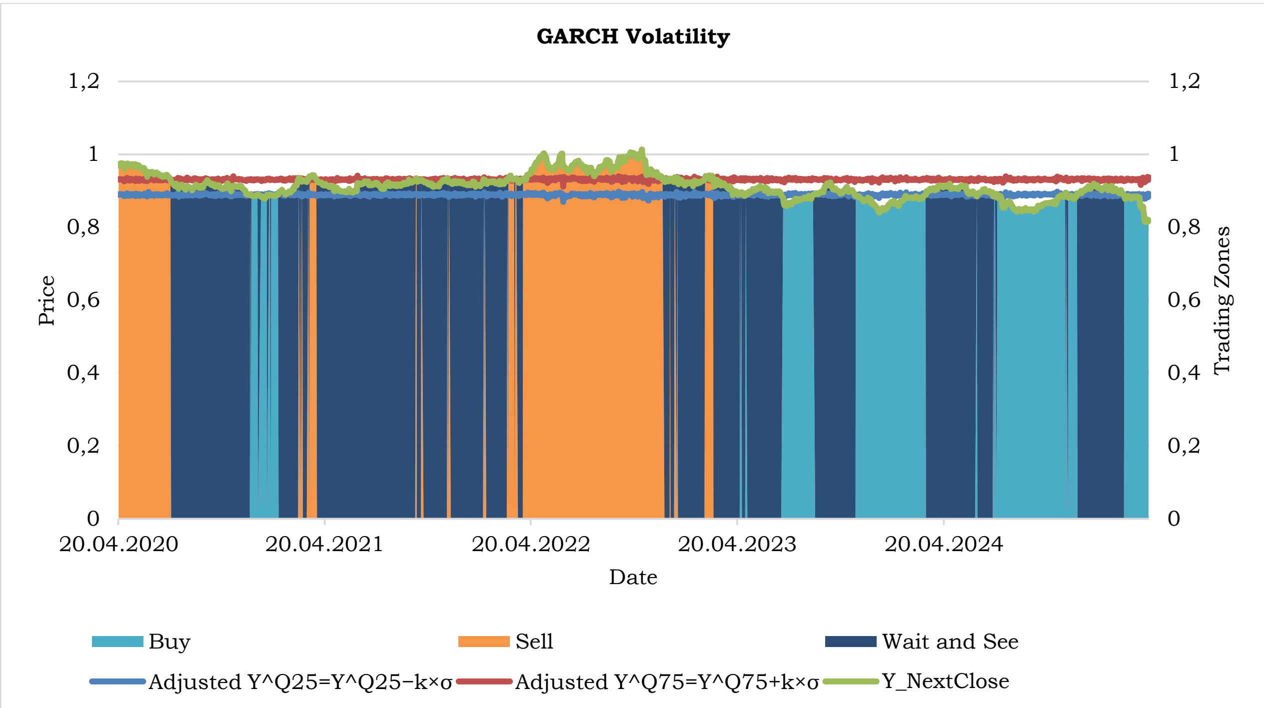
Figure 7. Distribution of Trading Strategy Signals Over Time



This bar chart, which is entitled as "*Trading Strategy*", states the frequency of "*Buy*," "*Sell*," and "*Wait and See*" signals which are generated from previously shown Plot-6 over an annual time period from 2020 to 2025.

This bar chart is designed to illutsrate how the signals that are derived by this approach can be implemented with keeping the perceptions as much as simple and refined from market noise. Particularly, in trading and investment fields, the compelling part for decision taking science is to quantify the data which is reflected with the price action. For instance, in this visual a decision maker can instantly understand the trends on pricings with defined periods.

Figure 8. GARCH Volatility-Adjusted Price Ranges and Trading Zones (2020-2025)



This chart, titled "*GARCH Volatility*," attempts to integrate GARCH (Generalized Autoregressive Conditional Heteroskedasticity) volatility-adjusted quantile levels with potential trading zones and the actual price of USD/CHF over time (Engle, 1982):

The chart elements are broken down with following order:

• X-axis (Date): Represents time, spanning from approximately 20.04.2020 to 18.04.2025 (consistent with previous charts).

• Left Y-axis (Price): Represents the price values, ranging from 0 to 1.2, used for the actual price (Y_NextClose) and the potential adjusted quantile levels.

• Right Y-axis (Trading Zones): Also ranges from 0 to 1.2 corresponds to the stacked areas representing "*Buy*," "*Sell*," and "*Wait and See*" zones.

• Stacked Area/Bars (Buy, Sell, Wait and See): Similar to the previous "*Supply and Demand Zones"* chart, these colored areas indicate different trading zones based on strategy along with the analysis.

Cyan (Buy): Potential buying opportunities.

Orange (Sell): Potential selling opportunities.

Dark Blue (Wait and See): Periods of indecision or no clear signal.

• Blue Line (Adjusted Y^Q25=Y^Q25-k*σ): Represents the 25th percentile (Q25) adjusted by subtracting a factor (k) times the GARCH-modeled volatility (σ). This creates a lower, volatility-adjusted bound.

• Red Line (Adjusted Y^Q75=Y^Q75+k*σ): Represents the 75th percentile (Q75) adjusted by adding a factor (k) times the GARCH-modeled volatility (σ). This creates an upper, volatility-adjusted bound.

• Light Green Line (Y_NextClose): Represents the actual USD/CHF closing price over time.

The blue and red lines together define a volatility-adjusted interquartile range. The distance between these lines expands during periods of high GARCH-modeled volatility and contracts during periods of low volatility. This aims to create more dynamic and adaptive trading signals or risk assessment levels. Observation can be explored with how the "*Buy*," "*Sell*," and "*Wait and See*" zones align with the volatility-adjusted quantile range. The trading strategy might be triggered when the actual price or the adjusted quantiles enter or exit these zones. The light green line (Y_NextClose) shows the actual price movement relative to the volatility-adjusted Q25 (blue) and Q75 (red) levels.

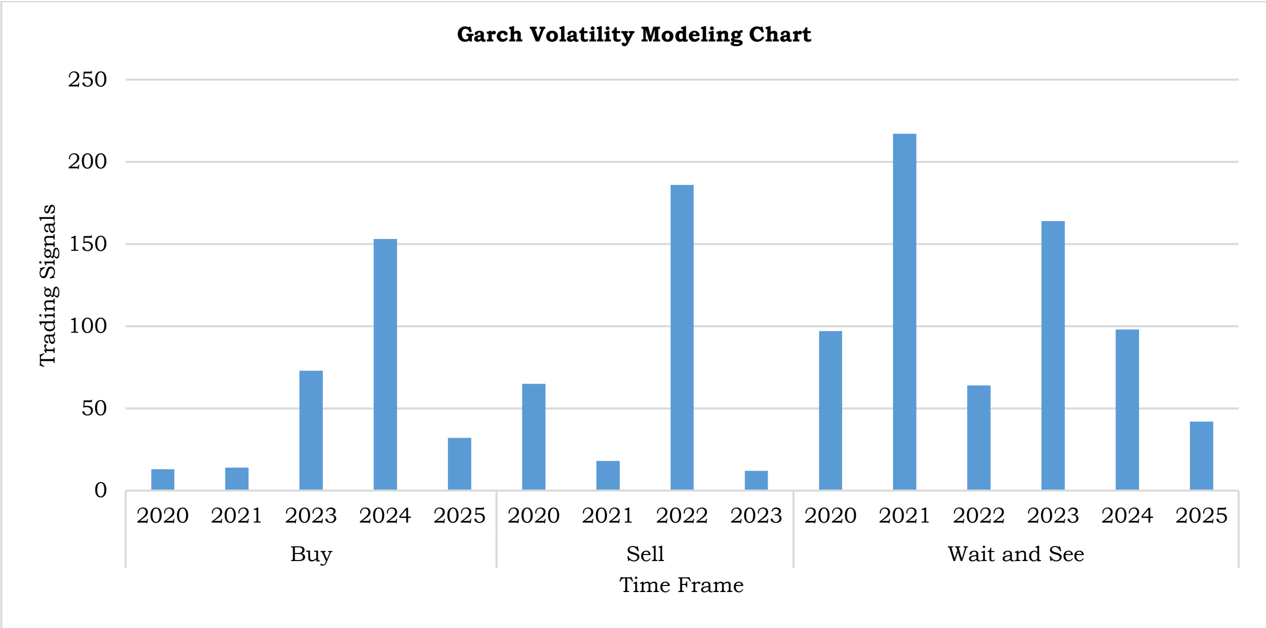
Buying opportunities might be favored when the price approaches or falls below the adjusted Q25. Selling opportunities might be favored when the price approaches or rises above the adjusted Q75. "*Wait and See*" zones might occur when the price is within the adjusted IQR.

By comparing this chart to the "*Actual Price vs Predicted Quantile Range*" chart, a person can see how incorporating GARCH volatility affects the predicted range and the potential trading signals. The volatility adjustment is performed to make the bands wider during turbulent periods and narrower during calm periods.

Visual assessments are served for if the trading zones and the volatility-adjusted quantile levels seem to provide useful signals for potential price movements. The testings are performed for the price tends to react in the expected direction after entering a "*Buy*" or "*Sell*" zone relative to the adjusted quantiles.

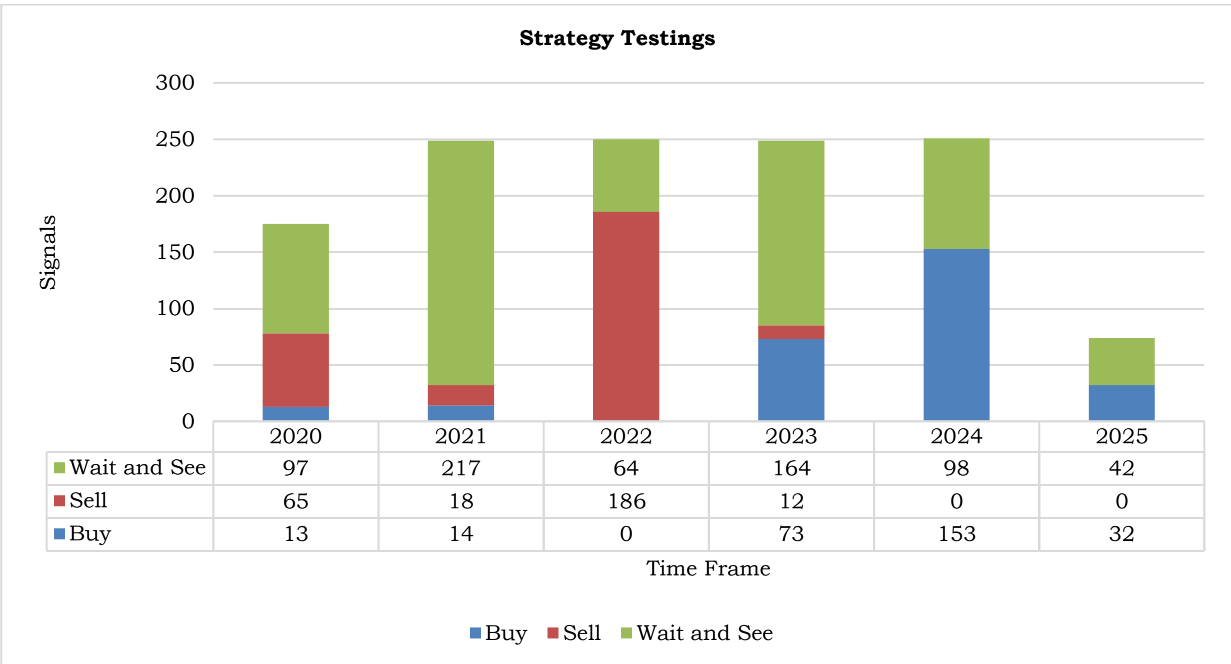
Volatility dynamics of the asset is patterned by the integration of GARCH-based model with residual distribution that support the signal processing for financial decision taking. Therefore, the illustration for a more adaptive approach of the decision taking in the predefined financial vehicle is implemented through GARCH-based modeling into the quantile framework, which allows Buy, Sell, and Wait-and-See signals to arrange depend on shifts in market conditions. The volatility adjusted bands are structured by scaling the parameters that are applied to these bandwidths, so by this way the trading risk can be reflected much realistically than static quantile zones.

Figure 9. GARCH Volatility Modeling: Distribution of Trading Signals by Year



"*Garch Volatility Modeling Chart*" provides that the frequency of trading signals generated by the strategy is affected by the GARCH-modeled volatility of the USD/CHF exchange rate. With in this context, periods of high signal frequency correspond to periods of high foreseeable volatility like perceived trading opportunities, while periods with more "*Wait and See*" signals indicate lower predicted volatility or higher uncertainty. Therefore, a further detailed comprehension of the algorithm of the strategy and a performance analysis are needed to totally assess the efficiency of integrating GARCH volatility modeling.

Figure 10. Annual Distribution of Trading Strategy Signals (2020-2025)

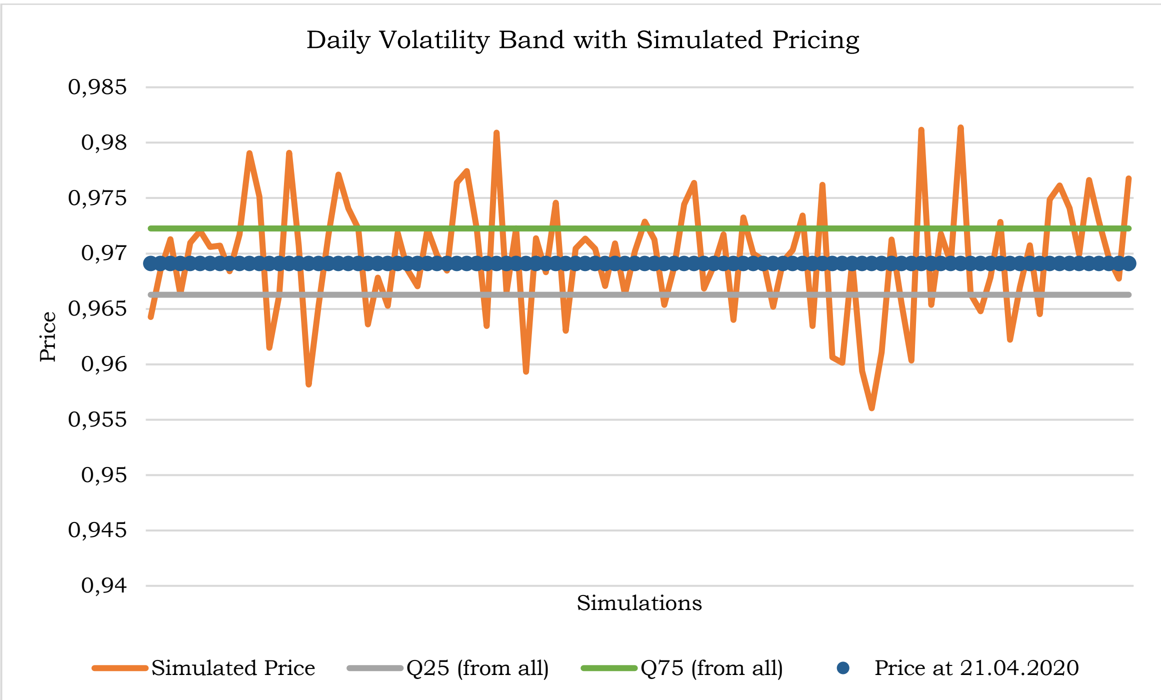


	2020	2021	2022	2023	2024	2025
Wait and See	97	217	64	164	98	42
Sell	65	18	186	12	0	0
Buy	13	14	0	73	153	32

The GARCH volatility modeling strategy for USD/CHF is formed to express the disparate annual biases between 2020 and 2025. At first, 2020 leaned towards bearish bias with dominant selling signals and a significant "*Wait and See*" stance, demonstrating a cautious bearish outlook. This caution strengthened in 2021, where a forceful amount of "*Wait and See*" signals and very few trading signals showed that the model largely forewarned to shun the market due to high ambiguity. A solid bearish conviction then appeared in 2022, pointed to the highest sell signal amount and minimum "*Wait and See*" actions. The strategy converted into a bullish perspective in 2023, with a significant spiral in buy signals, while a considerable count of "*Wait and See*" signals marked persistent alertness. This bullish sentiment maximized in 2024, which saw the uppermost frequency of buy signals and no sell signals, providing strong confidence in an upward trend. Finally, 2025 showed a decline in conviction, with fewer buy signals and a low "Wait and See" count, indicating a slightly bullish but overall subdued trading environment according to the model. The strongest bearish and bullish years were clearly 2022 and 2024, respectively, while 2021 represented the period of highest uncertainty and trading avoidance.

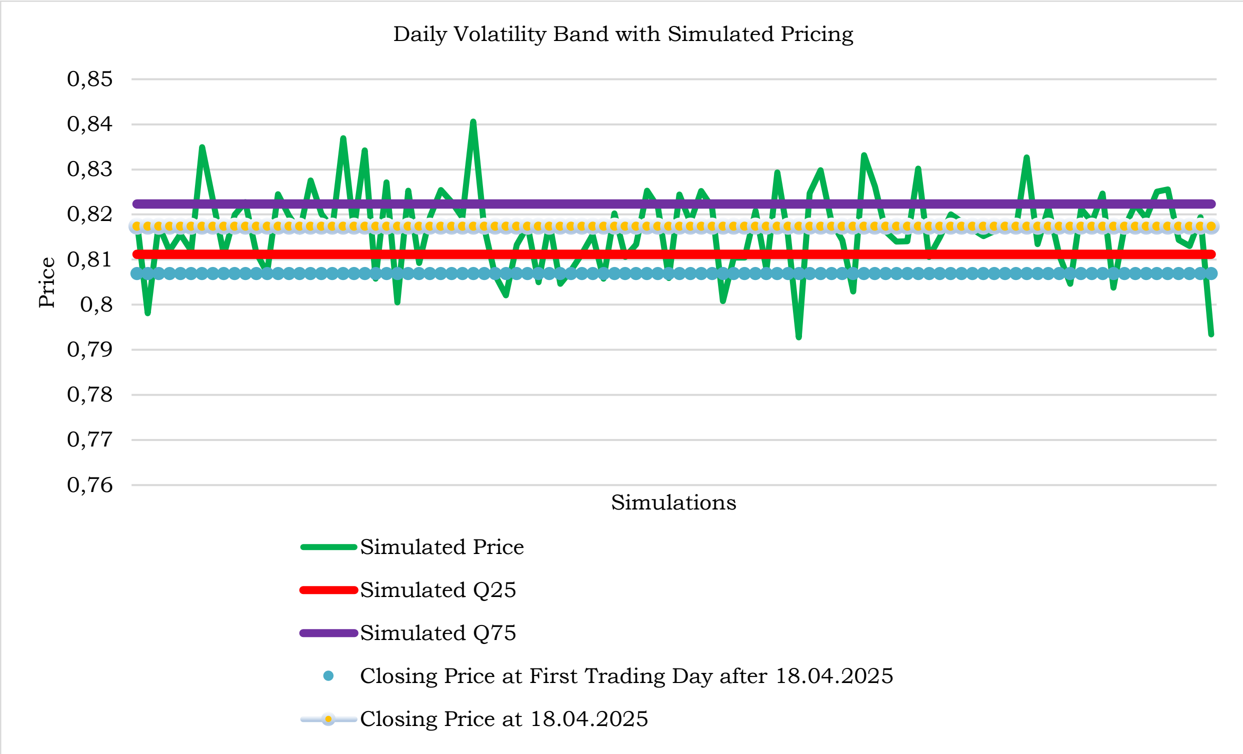
The use of a single predictor (Lag1_Return) is intentionally adopted to obtain the pure and unconfounded effect of short-term return dynamics on the next-day closing price within the quantile regression structure. Including additional macroeconomic or market-based control variables would have introduced multi-collinearity risks and masked the intrinsic return-to-return transmission mechanism that the study sought to isolate. Moreover, the primary objective is to examine whether short-horizon momentum or reversal effects could be captured directly through the most immediate lag, which is theoretically supported in high-frequency FX markets where information is rapidly priced in. For these reasons, a parsimonious, single-variable specification is preferred, allowing the quantile-specific behaviour of the USD/CHF series to be assessed without interference from external covariates. Future extensions may incorporate richer variable sets; however, the current design provides a clean baseline for identifying the fundamental predictive structure.

Figure 11. Simulated Daily Pattern for COVID-19 Period Backtesting



A pseudo design is used for backtesting of the Covid period which involves higher volatility conditions to assess the agility of quantile based simulation model. In this setting, the time frame which surrounds 21 April 2020, correspondent to one of the most turmoiled intervals in the market landscape, is uprooted and reckoned distinctly. So, a seperate simulated price tracer is derived for this purpose to compare values inside of the quantile focused volatility band. As a result of this operation, the stability of the model is examined under extreme market conditions. The simulated values show an acceptable consistency even if an extreme economic shock emerges like in Covid period.

Figure 12. Simulated Daily Price Paths and Predicted Volatility Ranges



In this case, the model expected the next day's price to remain within the central 50% prediction band defined by the Q25–Q75 volatility-adjusted quantiles, yet the actual closing level exceeded that range, indicating an unanticipated price swing. Such an outcome illustrates the model's partial limitations, particularly in capturing movements that occur in the distribution tails where less frequent but impactful deviations arise. This also emphasizes the role of tail risk in exchange rate forecasting and suggests that relying solely on lagged price behavior and GARCH-based volatility may not always be sufficient when market conditions shift sharply. To improve predictive sensitivity in these scenarios, expanding the model structure-such as integrating additional macro-financial factors, refining the volatility specification, or widening the quantile bands to better represent uncertainty-would be beneficial. Overall, while the model provided a reasonable estimate for 18.04.2025, its underestimation of the subsequent day's volatility demonstrates the need for ongoing adjustments to enhance performance during abrupt market changes.

4. Conclusion

The proposed quantile-based forecasting and optimization framework yielded several significant outcomes. First, the Quantile Regression models successfully captured asymmetric price behaviors across different quantile levels, allowing for a more nuanced understanding of probable next-day USD/CHF price zones. Monte Carlo simulations when combined with GARCH-based volatility inputs further enhanced the reliability of simulated price paths, especially under turbulent market conditions. The integrated optimization model, which utilized grid search and evolutionary algorithms, consistently outperformed static trading strategies by dynamically adjusting entry, take-profit, and stop-loss levels based on probabilistic intervals and volatility clustering. On average, backtested scenarios showed a noticeable improvement in expected returns and a measurable reduction in drawdown and transaction costs.

This study underpins the critical function of range-based evaluation in FX modeling and decision-making. Unlike conventional point predictions, probabilistic price zones, that are derived from quantile techniques and GARCH volatility indicator, present traders a more transformable and risk-attentive tool for performing trades. The harmony between volatility structuring and simulation-based optimization provided not only resilient estimations but also actionable entry/exit fields which are dynamic and sensitive to developing market risks. Additionally, the quantile-based system elicited specifically effective in capturing fat-tailed price behaviors, which are often neglected in mean-centric models. Despite everything, limitations akin to model sensitivity to hyperparameter adjusting and dependence on statistical data quality are explored which affirm further attention.

This framework could be enhanced by future researches through multi-currency valuations or cross-asset portfolios that are spanning correlated vehicles such as oil, gold or silver. The implementation of sentiment analysis of macroeconomic events into quantile estimation could also improve real-time interactivity. Moreover, application of reinforcement learning or deep quantile networks might further rejuvenate dynamic strategy customization, particularly subject to regime shifts for pivotal zones. Finally, real-time deployment and stress-testings in high-turbulent conditions would confirm operational feasibilty to broaden the utility of this method for institutional-level trading systems.

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Author Contributions Statement: Nearly all stages of the study-topic selection, research design, data analysis, and interpretation of the findings-were carried out by the author. During the manuscript preparation stage, artificial intelligence (AI) (ChatGPT) was used in a limited and measured manner (approximately 20% at minimum) for partial editing, and improvements were made accordingly.

Conflict of Interest Statement: The author declares that there is no conflict of interest regarding this study.

Research and Publication Ethics Statement: All rules specified in the "*Higher Education Institutions Scientific Research and Publication Ethics Directive"* were followed at every stage of this research. None of the actions specified under the heading "*Actions Contrary to Scientific Research and Publication Ethics"* of the directive were carried out. During the writing process of this study, citations were made in accordance with ethical rules, and a bibliography was created. The study was subject to plagiarism control.

Ethics Committee Approval: Since the study is based on secondary data, ethics committee approval is not required.

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