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A comparative analysis of quantile regression models in predicting stock returns under extreme market conditions.

Author(s): Ciline Ghribe
Supervisor(s): Leonardo Iania
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Signed in Louvain-La-Neuve on January 8, 2026

Ciline Ghribe

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1 Introduction

The question of whether and how asset returns can be predicted has long stood at the core of financial economics. Return prediction is not only fundamental to understanding market efficiency but also essential for asset allocation, risk management, and the development of pricing models (Campbell & Viceira, 2002). While the Efficient Market Hypothesis (Fama, 1970) suggests that returns should be largely unpredictable, decades of empirical research have documented that certain financial and economic indicators contain information about future market performance (Campbell & Shiller, 1988; Lettau & Ludvigson, 2001). These insights have shaped how both academics and practitioners approach asset allocation and understand market dynamics.

Much of the foundational work in return predictability has benefited from markets with long and consistent timeseries data, but the European stock market presents distinct economic and financial features that justify a focused analysis. Over the past decades, the euro area has undergone profound structural changes including the creation of the monetary union, sovereign debt pressures, shifts in monetary policy frameworks, and pronounced episodes of financial volatility. Thus, understanding whether these macro-financial variables hold predictive content for European equities is therefore essential for interpreting market behavior, assessing risk, and refining empirical asset-pricing models that operate within this economic environment.

Traditional linear regression models have provided mixed and often unstable evidence of predictability in the stock market context, largely because they estimate a single average relationship across the entire distribution of returns. Yet financial market behavior is rarely uniform because tail events, asymmetries, and nonlinear responses are fundamental features of asset returns. Variables that appear uninformative in average conditions may exert significant influence during market downturns or episodes of heightened uncertainty. This suggests that models capable of distinguishing between different parts of the return distribution may offer a more accurate and complete representation of how macro-financial factors interact with equity markets. (Dangl & Halling, 2012; Ma & Pohlman, 2005; Demirer et al., 2017).

Quantile-based methods have therefore gained prominence as a natural extension of traditional predictive frameworks. Quantile Regression (Koenker & Bassett, 1978) allows the effect of predictors to vary across market states, uncovering heterogeneous relationships that would otherwise be obscured in mean-based models. The emergence of Bayesian Quantile Regression further incorporates parameter uncertainty into the estimation process, while time-varying quantile methods make it possible to trace how these relationships evolve across economic regimes and crisis periods. Together, these approaches provide a richer toolkit for examining return predictability in settings characterized by structural change, asymmetry, and tail-driven dynamics.

Against this background, the present study investigates whether macro-financial variables predict the entire distribution of monthly returns of the STOXX Europe 600 index and whether these predictive relationships differ across the return distribution and over time. By employing three different frameworks classical Quantile Regression, Bayesian Quantile Regression, and Time-Varying Quantile Regression the analysis explores both the cross-sectional and temporal dimensions of predictability, offering a comprehensive assessment of the stability, asymmetry, and economic relevance of macro-financial effects in the European equity market.

Within this methodological and conceptual framework, the study is guided by a central research question:

"To what extent do macro-financial variables predict the tails of monthly returns of the STOXX Europe 600 index?"

Focusing on the tails rather than the mean is crucial for understanding how markets behave under stress or strong expansion, where risks and opportunities are most consequential. Studying tail predictability also allows the analysis to evaluate whether macro-financial conditions influence extreme returns differently from moderate ones, which is particularly relevant in a European market shaped by recurring crises and shifting monetary environments.

To address this overarching question, two sub-questions structure the empirical investigation:

1. Does the impact of macro-financial variables change across extreme quantiles, and if yes, to what extent?
   This examines whether predictors matter more during downturns, normal periods, or exceptional market upswings.
2. Which modelling framework performs best in-sample?
   By comparing classical QR, Bayesian QR, and Time-Varying QR, the study evaluates whether incorporating uncertainty or allowing coefficients to evolve over time improves predictive accuracy.

Based on the theoretical arguments and empirical patterns documented in the literature, two hypotheses are formulated:

Hypothesis 1: *The impact of macro-financial variables on stock returns is non-linear and becomes more pronounced in the extremes of the return distribution.* This reflects the idea that downside and upside markets react differently to macro-financial conditions.

Hypothesis 2: *The time-varying model outperforms static models in-sample.* If relationships between predictors and returns shift across economic regimes, then flexible models that adjust over time should yield superior quantile forecasts.

These questions and hypotheses put the study in a position to evaluate predictability's existence as well as its stability, asymmetry, and dependence on changing macroeconomic circumstances. The analysis advances a more complex understanding of return dynamics in the extreme European stock market by combining distributional and temporal dimensions.

1.1 Research Contribution

This study contributes to the literature on return predictability in several important ways. First, it provides a comprehensive examination of how key macro-financial variables such as volatility, inflation, the term spread, oil prices, and industrial production affect European stock returns across the entire return distribution rather than only on average. Most existing research relies on mean-based predictive models, but this study uses a quantile-based framework that reveals heterogeneous and asymmetric effects that cannot be detected with traditional approaches with a particular focus on lower (e.g., 5th, 10th) quantile and upper (90th, 95th) quantiles. By identifying the specific parts of the return distribution in which each predictor becomes relevant, whether during severe downturns, normal market conditions, or exceptionally strong months, the analysis deepens our understanding of state-dependent predictability in the euro-area equity market.

Second, the study incorporates a time-varying perspective to evaluate whether predictive relationships remain stable or evolve across different macroeconomic environments. The use of Time-Varying Quantile Regression allows the analysis to identify periods in which macro-financial variables gain or lose predictive strength, such as during financial crises, inflationary episodes, or post-crisis recoveries. This dynamic evidence fills an important gap in the existing literature, which often relies on static models that assume constant relationships over time.

Third, the study contributes methodologically by comparing three different modelling frameworks: classical Quantile Regression, Bayesian Quantile Regression, and Time-Varying Quantile Regression. This comparison makes it possible to assess the robustness of predictive signals and to evaluate how sensitive the results are to modelling assumptions and strengthens the empirical conclusions and highlights the importance of treating return predictability with appropriate caution.

Finally, by applying this multi-model quantile-based analysis to the STOXX Europe 600 index over a recent sample, the study offers a unified and up-to-date assessment of macro-financial return predictability in the European context. It combines distributional, temporal, and uncertainty-aware perspectives, providing a more complete picture of how European equity returns respond to macro-financial conditions.

The remainder of the thesis is structured as follows. Section II provides an overview of the literature on return predictability and quantile-based methods. Section III presents the data and methodological procedures. Section IV reports the empirical findings for QR, BQR and TVQR and discusses the results. Section V tackles the limitations of this study and further research options. Finally, Section VI concludes the paper.

2 Literature Review

This section explains how the return-predictability literature moved from traditional linear, mean-based models to distribution- and time-sensitive approaches. It is organized in four steps. First, it reviews why OLS and other linear regressions became the standard tools in asset-pricing research and what their key assumptions imply. Second, it shows why these assumptions are often violated in financial data, through heteroskedasticity, non-normality, tail events, and parameter instability, so that average (mean) effects can mask state-dependent relationships. Third, it introduces quantile regression (QR) as an alternative that estimates effects across the full return distribution (especially the tails). Fourth, it presents two extensions used in this study the first being Bayesian QR, which emphasizes parameter uncertainty, and the second being time-varying QR, which allows coefficients to evolve across regimes. Finally concluding with supporting evidence from European market applications.

2.1 Overview of Traditional Linear Models for Return Prediction

The question of whether and how future asset returns can be predicted has long stood at the core of financial economics. Return prediction is not only fundamental to understanding market efficiency but also essential for asset allocation, risk management, and the development of pricing models. Despite the dominance of the Efficient Market Hypothesis introduced by Fama in 1970, which posits that excess returns cannot be predicted, the 1980s witnessed a dramatic increase in the academic literature on return predictability, especially due to the rising interest of researchers and economists that has accumulated over the previous years, aiming to identify how stock returns and fundamentals are related (Banz, 1981; Shiller, 1981; Fama & French, 1988b; Keim & Stambaugh, 1986; Chen et al., 1986; Campbell & Shiller, 1988). Then, throughout the 1990s, researchers shifted from documenting predictability to understanding its economic sources (Fama, 1990; Fama & French, 1992; Lettau & Ludvigson, 2001).

During this period, researchers relied on linear regressions frameworks, mostly the Ordinary least Square (OLS), to conduct their research on asset pricing and return predictability. For instance, Shiller (1981) employed linear regressions to examine excess volatility and the predictive content of dividend–price ratios, Rozeff (1984) ran OLS predictive regressions showing that dividend yields forecast future returns, Keim and Stambaugh (1986) applied OLS regressions to link expected risk premia to interest-rate–based predictors, Chen et al., (1986) estimated macroeconomic factor exposures and conducted linear Fama–MacBeth cross-sectional tests, Campbell & Shiller (1988) relied on OLS predictive regressions and linear VAR models to show that valuation ratios forecast long-horizon returns, and Fama & French (1992) employed linear Fama–MacBeth regressions to demonstrate that size and book-to-market characteristics explain the cross-section of returns as well as Lettau & Ludvigson (2001) who used standard OLS predictive regressions and a linear VAR to show that the consumption–wealth ratio contains powerful information about expected stock returns.

The reason why researchers relied on the Ordinary Least Squares (OLS) is because of its practicality and several desirable properties. In fact, under the classical Gauss–Markov conditions, OLS estimators are best linear unbiased estimators (BLUE) (Van Bellegem, 2022, pp. 12, 83-84) i.e., among all linear unbiased estimators, they have the smallest variance. In addition, it's computationally straightforward, easy to interpret, and aligns neatly with the linear structure of early asset-pricing models like the Capital Asset Pricing Model (CAPM).

In Fact, the OLS framework relies on several assumptions that, when they all hold, ensure the validity, interpretability and statistical reliability of its estimates. One fundamental assumption is linearity between dependent and independent variables, meaning that the expected change in the outcome associated with a one-unit change in a predictor is constant and can be summarized by a single coefficient. This automatically suggests that coefficients are constant and the relationship between dependent and independent variables does not shift across different periods or regimes within the sample. (Van Bellegem, 2022, pp. 9-10)

Another important assumption is homoskedasticity, which states that the variance of the regression error terms, usually represented as ε, should be constant across all observations. Only when the variance is the same across all values of the predictors, OLS gives the smallest possible standard error for the coefficients. Otherwise, when error terms are heteroskedastic the OLS estimates would remain unbiased but would no longer guarantee optimality (no longer BLUE) and their usual standard error formula becomes invalid. Additionally, OLS assumes that the regression error follows a normal distribution as it facilitates precise statistical testing by ensuring that t- and F-statistics follow their theoretical sampling distributions. (Van Bellegem, 2022, pp. 9-10)

2.2 Traditional Models Limitations & Financial Data Behavior

These assumptions imposed by OLS expose this framework to meaningful drawbacks once it is to be applied upon financial data. Thus, the consequences of choosing an inappropriate modeling approach leads to persistent gaps in knowledge, which in turn result in inaccurate risk forecasts and inefficient capital allocation, potentially exacerbating financial instability (Chavleishvili et al., 2023). These concerns become especially pronounced during times of systemic crisis as history has repeatedly shown that major shocks such as the 2008 financial crisis the Euro Sovereign Debt Crisis generate extreme negative returns and highly elevated volatility that are not well captured by Gaussian-based or constant-parameter forecasts. As empirical work on return predictability expanded, evidence accumulated showing that equity returns and fundamentals behave in ways fundamentally inconsistent with the assumptions that are the essence of traditional linear, mean-focused frameworks. In particular, the core assumptions of normality, homoskedasticity, and linearity inherent in ordinary least squares (OLS) regression are frequently violated in financial data (Gilli & Schumann, 2010). In fact, financial time-series often exhibit volatility clustering, heavy tails, and structural breaks, and because OLS estimators are highly sensitive to outliers and extreme observation, all the above result in biased or inefficient estimates, especially in the tails of the distribution. As a result, OLS-based models offer limited robustness and accuracy in capturing tail risks and extreme return behavior (Pohlman & Ma, 2008; Reidel, 2014; Bekiros & Gupta, 2015). A closely related argument is developed by Bassett & Chen (2002) which shows that summarizing the impact of explanatory variables with a single coefficient is conceptually misleading. The paper demonstrates that factor exposures can affect different parts of the return distribution in opposing ways, so that large positive and negative tail effects may cancel out at the mean.

Riedel (2014) pushed the literature further showing that extreme downside risk is distinctly priced and exhibits a non-linear, regime-dependent relationship with returns. His findings reveal that tail risk carries a significant return premium, particularly during crisis periods, and that this effect is undetectable when relying solely on variance or mean-based estimators. He emphasizes that traditional linear frameworks miss these dynamics, which are driven by asymmetric tail dependencies and structural shifts in market regimes. Similarly, Rapach and Zhou (2012) note that structural breaks, business-cycle asymmetries, and shifts in risk premia weaken the usefulness of OLS-based forecasts, which rely on stable conditional mean relationships; instead, return predictability is found to be episodic, state-dependent, and often strongest in the tails of the distribution.

Adrian et al. (2019) developed the "vulnerable growth" framework, a nonlinear and regime-switching approach, to show that financial conditions predict downside macroeconomic risks differently depending on the prevailing regime. Their model explicitly captures the state-dependent nature of predictive relationships, allowing the impact of financial variables on growth and returns to vary across calm and stressed environments. Fromentin (2022) reached similar conclusions using a rolling-window Granger causality framework, revealing that the causal relationship between macroeconomic indicators and stock returns is highly unstable, especially during crisis periods. This instability is not simply noise, in fact it reflects meaningful shifts in the underlying economic structure, suggesting that fixed-coefficient models are often inadequate precisely when accurate prediction is most needed.

2.3 Alternative Approaches

Quantile regression (QR) extends classical least-squares by estimating conditional quantile functions instead of the mean. Koenker and Bassett (1978) introduced QR to capture the effects of predictors on different points of the outcome distribution, rather than assuming a homogeneous impact on the mean. In asset pricing applications, this means we can study how predictors affect the tails of stock returns (e.g. crash and boom scenarios) as well as the center. QR "allows us to examine specific parts of the return distribution such as the tails and the center" (Pedersen, 2010, p21) tracing out the entire conditional distribution of returns. This richer perspective can significantly improve insights and fill the knowledge gap that means models remains unable to deliver (Zhu, 2012).

Empirical studies have also confirmed QR's usefulness for stock return predictability. For example, Cenesizoglu and Timmermann (2008) were among the first to apply QR to U.S. equity returns. In their study they regressed the S&P 500 on lagged predictors and found significant predictability across the full distribution (in- and out-of-sample). Pedersen (2015) similarly uses QR to predict the distribution of U.S. stock and bond returns. His framework regresses return at many quantiles on a broad set of economic state variables, allowing location shifts, volatility and skewness effects to vary by quantile. Pedersen reports that forecasts based on quantile estimates outperform Gaussian-based mean forecasts, confirming that tail-specific models yield better density forecasts. Demirer *et al.* (2016) apply a "quantile boosting" algorithm to select among many predictors for U.S. returns. They find that short-term returns are only predictable in the extreme lower quantiles (bear-market states), whereas bullish tails show little predictability. Moreover, variables like short interest and sentiment add no predictive power once tail behavior is considered. Likewise, C. Ma *et al.* (2018) show that investor sentiment significantly predicts stock returns at low quantiles (crash states) but not at high quantiles, illustrating QR's ability to reveal asymmetric predictor effects that mean regressions miss.

Across studies, the set of predictors examined is very broad: traditional financial ratios (dividend yields, earnings-price, term spreads, etc.), macroeconomic indicators (inflation, consumption-wealth ratios, business cycle indices), market volatility measures (VIX, realized volatility), and sentiment indices are all used in QR setups. Zhu (2013) notes that in a quantile regression of the Russell 1000 and bond returns on "a range of economic state variables," many variables have significant but heterogeneous effects across quantiles (especially for bonds). In short, QR studies allow each predictor's slope to vary with the quantile, capturing how, for instance, high interest rates might strongly depress left-tail returns but have little effect on the median.

Another advantage of QR is its adaptability, serving as a foundation for more advanced models such as Bayesian Quantile Regression and Time-Varying Quantile Regression. These extensions improve QR's capacity to integrate uncertainty, parameter dynamics, and nonlinear relationships while maintaining its intuitive interpretability.

2.3.1 Bayesian Framework for QR

Bayesian Quantile Regression (BQR) embeds the QR framework within a Bayesian inference scheme. In practice, one assumes an asymmetric Laplace likelihood as in Yu & Moyeed, (2001) and places priors on the regression coefficients. This yields a full posterior distribution for the quantile slopes and intercepts, allowing interval estimates and easy incorporation of prior information. A major benefit is robustness in small samples and under model uncertainty: Bayesian methods can stabilize estimation via shrinkage priors and avoid overfitting, while automatically quantifying uncertainty in predictor inclusion. For example, Alhamzawi and Yu (2012) propose a Bayesian adaptive Lasso for quantile regression, assigning independent inverse-gamma hyperpriors to Lasso penalties for each coefficient. By letting the data estimate the penalty hyperparameters, their method adaptively shrinks noise coefficients and enhances sparse estimation (Alhamzawi et al., 2012). Such hierarchical priors make BQR especially useful when many predictors or potential structural breaks make the model uncertain.

Indeed, Kozumi and Kobayashi (2011), Iacopini et al. (2023) Alhamzawi et al., 2012, and other researchers have shown that Gibbs samplers can efficiently estimate BQR models by exploiting a scale-mixture-of-normals representation of the asymmetric Laplace. In finance, BQR has been applied to risk and tail forecasting. For instance, Gerlach et al. (2010) develop a Bayesian time-varying quantile model to forecast market Value-at-Risk (VaR), demonstrating that allowing quantile parameters to evolve (with stochastic volatility) yields improved tail forecasts. Carriero *et al.* (2022) and Clark and Ravazzolo (2015) similarly show that Bayesian quantile methods with stochastic volatility capture the extreme "Growth-at-Risk" behavior in U.S. GDP and financial indicators (of which stock returns are a component).

In short, the Bayesian framework yields richer inference (posteriors for each quantile slope) and tends to produce more stable estimates than purely frequentist QR, especially in small samples or near the tails.

2.3.2 Time-Varying Framework for QR

Quantile regression (QR) generalizes mean models by estimating conditional return distributions, capturing heterogeneity and tail risk that linear models miss. However, static QR assumes fixed coefficients, ignoring evolving market conditions. In practice, parameters often shift due to monetary policy, sentiment, or regime changes. Indeed, Dangl and Halling (2012) emphasize that "parameter instability (time-variation in coefficients) represents a major challenge" in return predictability. Time-varying QR (TVQR) thus embeds QR in a dynamic framework so that coefficient effects on different quantiles can adapt over time.

This framework has been applied across global equity markets and periods, often focusing on crisis episodes or volatile regimes. An influential methodological contribution in this context is Cappiello et al. (2005), published as ECB Working Paper No. 501, which introduces a semi-parametric framework for modeling time-varying regression quantiles and their implications for financial comovements. Importantly, the authors show that apparent increases in correlations during crises can be misleading once heteroskedasticity is accounted for, reinforcing the need for quantile-based, time-adaptive methods.

Meligkotsidou *et al.* (2012) develop a QR framework for the US equity premium using many predictors. They form quantile forecasts for the premium and then combine them via time-varying weights to produce point forecasts. This dynamic weighting of quantile predictions "delivers statistically and economically significant out-of-sample forecasts" (Meligkotsidou et al., 2012) that beat both the historical mean and conventional regression combinations. In other words, leveraging the full conditional distribution with time-varying synthesis improves prediction of the equity premium. Meligkotsidou *et al.* (2012) also report that their time-varying QR approach produces higher utility gains for investors than static predictors.

Focusing on crises, Chevapatrakul *et al.* (208) examine how a time-varying tail-risk measure predicts US market returns via QR. They find that higher tail risk strongly predicts higher future returns at the *lower* quantiles, especially at one-month horizon. In contrast, tail risk has no predictive power in the upper half of the return distribution. In sum, quantile regression reveals an asymmetric effect, that is, tail risk matters primarily in "bear" states. This confirms that TVQR can capture structural shifts, in this case, investors demand extra return after bad times, something that linear models miss.

Overall, the TVQR literature demonstrates that return predictability and financial dependence are inherently dynamic and asymmetric. Time-varying quantile models provide a flexible framework capable of capturing evolving risk premia, crisis-driven comovements, and tail-specific predictability. The methodological foundations laid by Cappiello et al. (2005), combined with subsequent empirical applications, support the view that TVQR approaches offer a more accurate and economically meaningful representation of stock return dynamics than static or mean-based models, particularly when the focus lies on extreme outcomes and financial stability.

2.4 Evidence from The European Market

While the advantages of QR-based methods are general, it is worth noting their successful application in European market contexts and how they provide insights relevant to broad indices like the STOXX Europe 600. For instance, in one study conducted by Baur et al. (2011) quantile regression has been applied to analyze the distribution of European stock returns, the study examined daily, weekly, and monthly returns of the 600 stocks in the STOXX Europe 600 index (1979–2009) and explicitly contrasted mean-based vs. quantile-based analysis. They found that focusing only on the conditional mean could miss important dynamics. The quantile approach revealed an S-shaped pattern of return autocorrelations across quantiles, meaning lower-tail returns exhibited positive autocorrelation while upper-tail returns showed negative autocorrelation, even though at the mean there was little to no autocorrelation (Baur et al., 2011). The empirical findings of Aslanidis, Christiansen, and Savva (2021) provide further support for the value of quantile approaches in European settings. Using daily data for nine Eurozone stock markets (1999–2020), they estimate a quantile risk–return trade-off using the VSTOXX as the risk measure. Their results show a significantly negative risk–return relationship in the lower tail and a significantly positive relationship in the upper tail while the median displays no significant effect, exactly mirroring their findings for the U.S. market. These results underscore that risk–return dynamics in Europe are strongly asymmetric, with tail behavior fundamentally different from the center of the distribution. Such nonlinearities would be invisible in an OLS framework that imposes a single average effect (Aslanidis et al., 2021).

Another area of European-focused research is “growth-at-risk” and macro-financial tail risk assessment, which heavily relies on quantile regression. The European Central Bank and others have adopted quantile regression and quantile vector autoregressions to study how financial conditions impact the downside tail of GDP growth (Chavleishvili et al., 2023). The allure of these QR-based methods is precisely that they “allow for modeling tail risk conditional on variables, just like one would do for the mean, but without assuming symmetry” (Szendrei & Varga, 2023, p1) nor linearity when modeled by TVQR. This approach aligns naturally with risk-oriented policy analysis frameworks (Cecchetti, 2008; Cecchetti and Suarez, 2021) by shifting attention from average outcomes to the lower tail of the distribution. By prioritizing the 5th percentile of growth (or asset returns) as the object of interest, policymakers can quantify worst-case scenarios under different predictor values and directly assess economic vulnerability under adverse conditions.

3 Methodology & Data

The first part of this section gives some insights about data collection and its various sources. The second part presents the 3 preparatory steps required before applying the model and generating the results, Finally, the third part focus on explaining the construction of the regression models and producing of visualizations that will be used to present and display results once the models are ran.

3.1 Data Collection & Description

3.1.1 Explained variable

The dependent variable of this study is the monthly return data calculated from the STOXX Europe 600 index, a broad European stock market index that was obtained from Investing.com. According to STOXX Ltd. (2025) *"With a fixed number of 600 components, the index provides extensive and diversified coverage across 17 countries and 11 industries within Europe's developed economies, representing nearly 90% of the underlying investable market."*. Thus, by modeling the return predictably of the STOXX 600 this study would essentially be testing how well macro-financial indicators predict the overall European stock market movement.

The STOXX 600 data were collected as price points, thus, to compute returns, the study employs log-difference method that is defined as the first difference of the natural logarithm of consecutive closing prices.

3.1.2 Explanatory Variables[1]

Turning to the explanatory variables, multiple predictors identified as significant and theoretically relevant were selected from various publicly available online database:

- Federal Reserve Bank of St. Louis (FRED): GDP, Long-term Interest Rates & Short-Term Interest Rates (for the calculation of the Term Spread variable) and Oil Prices.
- European central bank (ECB): Inflation, Industrial Production, Yield Curve Spot
- Stoxx.com: volatility (VSTOXX)

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[1] To strengthen the robustness of the regression results, the longest feasible time-series sample was retained. As a result, the GDP and Yield Curve Spot variables were excluded because their data coverage was too limited, leading to a final sample spanning January 1999 to August 2025.

Before testing, the data were cleaned and small gaps were filled using interpolation, LOCF, and backward fill. All variables were then consolidated into a single Excel file to form the final dataframe for analysis in RStudio.

3.2 Data Manipulation

3.2.1 Stationarity

A stationarity test is a crucial step as stock returns are often weakly stationary, and the macroeconomic and financial predictors used to forecast them such frequently display non-stationary behavior (Campbell & Thompson, 2008). Non-stationarity is, essentially, the tendency for key statistical properties like the mean and variance to change over time which may cause to biased estimates, false inference, and poor predicting performance if not accounted for. Therefore, Augmented Dickey-Fuller (ADF) tests were applied upon all variables and showed that in addition to the STOXX 600 index 3 explanatory variables were nonstationary, including, Term Spread, Industrial Production and Oil Prices.

Proper transformations, described below, were applied to ensure stationarity for the other 3 variables.

- STOXX 600: The index (expressed in prices) was transformed into continuously compounded log-returns:

$$r_t = \ln(P_t) - \ln(P_{t-1})$$

Where r_t denotes the continuously compounded return at time *t*, P_t is the closing price of STOXX 600 index at time t and P_{t-1} is the closing price of the previous period. This transformation removes the unit root and produces a stationary return series. (see Figure 5)

- Term Spread: It exhibited non-stationarity in levels; therefore, it was differenced once:

$$\Delta TS_t = TS_t - TS_{t-1}$$

Where ΔTS_t is one-period change in the term spread, and the time-index notation follows the same convention as previously defined. This removes trend persistence and stabilizes the mean. (see Figure 6)

- Industrial production: the index is expressed in levels, and was transformed into month-on-month change using log-difference:

$$IP_t = \ln(IP_t) - \ln(IP_{t-1})$$

Where IP stands for Industrial production and the notation follows the same convention as previously defined. (see Figure 8)

- Oil price: To obtain an economically meaningful measure of oil price movements, the series was transformed using log-differences.

$$OP_t = \ln{(OP_t)} - (0P_{t-1})$$

Where OP stands for Oil Prices and the notation follows the same convention as previously defined. (see Figure 7)

Inflation and volatility are kept in levels. (see Figure 9 & Figure 10)

3.2.2 Collinearity & Multicollinearity

Although quantile regression captures nonlinear effects of predictors across the distribution of return, the underlying model is still linear in its parameters "β" which makes it sensitive to collinearity, and high redundancy between regressors can produce unstable coefficient estimates, particularly in the tails. Therefore, inspecting pairwise correlations and multicollinearity is standard practice in empirical asset-pricing studies (Welch & Goyal, 2007; Rapach & Zhou, 2013).

A preliminary correlation test was carried out on the transformed dataset to examine the linear relationships between stock returns and the explanatory variables in addition to the co-movement among the predictors themselves. The results show that none of the pairwise correlations exceed |0.35| (see Figure 1 & Table 1) which is well below the common threshold of |0.80| that signals for multicollinearity concerns. These low magnitudes indicate that each predictor retains distinct informational content and that no variable is redundant.

Complimentarily to the correlation analysis, multicollinearity was also assessed using Variance Inflation Factors (VIF) with results varying between 1.002 and 1.12 (see Table 2), which is far below the conventional thresholds of 5 or 10. and confirms that the explanatory variables are not linearly dependent on one another.

Together, the correlation matrix and VIF diagnostics confirm that the set of macroeconomic and financial variables is appropriate for modelling and suitable for investigating return predictability under extreme market conditions through quantile regression approaches.

3.2.3 Heteroskedasticity & Normality

The last diagnostic step revolves around normality, where the Jarque–Bera test was carried out, for that matter, the conclusion strongly rejects the null hypothesis of normality (see Table 3), and the skewness indicates moderate negative symmetry meaning that the distribution of STOXX 600 returns has a heavier left tail. (see Figure 2) The excess kurtosis statistics also confirms that the distribution of returns deviates from the Gaussian benchmark (see Figure 3). This is consisted with the well-documented prior beliefs in the financial literature that financial returns exhibit asymmetry and heavy tails (see Figure 4), hence the need for modelling frameworks such as quantile approaches that explicitly account for non-normal and tail-dependent behavior.

3.3 Prediction Models

3.3.1 OLS

The benchmark model is a basic linear regression where STOXX 600 monthly log-returns are explained by five macro-financial indicators. It relies on ordinary least squares but estimated with heteroskedasticity-robust standard errors. It provides an overall view of how stock returns move with oil prices, term spread, real economic activity and inflation across the entire sample. OLS is used because it is still the standard baseline in empirical finance, easy to interpret and useful as a reference point before turning to the more flexible quantile approach.

The robust model is applied here because financial return series rarely display a stable level of volatility and periods of stress or calm can create large swings in variance. If this feature is ignored the usual OLS standard errors may give a misleading impression of how precise the estimates really are. Robust standard errors adjust the uncertainty around each coefficient so that statistical tests remain reliable even when volatility changes through time. Hence why the significance (p-value) may appear smaller (bigger p-value).

3.3.2 Quantile Regression

The classical quantile regression approach, firstly introduced by Koenker and Bassett (1978), is the departing point of the predictive models budling, where analyzing heavy tail behavior and extreme events (outliers) are of primary interest. To that matter, unlike OLS, the QR approach offers advantages for studying the relationship between extreme macro-financial variables and stock return especially during periods of financial distress, it allows better insights into how their effect differs at different parts of the stock return distribution via the possibility it provides to model these various effects explicitly. Given a dependent variable of interest and a set of explanatory macroeconomic and financial predictors, the τ-th conditional quantile of returns is formally defined as:

$Q_{r_t}(\tau|X_t) = X_t^T \beta(\tau),$

where X_t denotes the vector of predictors for month t, and $\beta(\tau)$ is the vector of quantile-specific coefficients.

Thus, the quantile regression model estimated in this study for a given quantile τ is expressed as:

$Q_{r_t}(\tau|X_t) = \beta_0(\tau) + \beta_1(\tau) \cdot V_t + \beta_2(\tau) \cdot TS_t + \beta_3(\tau) \cdot OP_t + \beta_4(\tau) \cdot I_t + \beta_5(\tau) \cdot IP_t + \varepsilon_t(\tau),$

Where V_t TS_t, OP_t, I_t, IP_t, respectively designate Volatility Term Spread, Oil Prices, Inflation, and Industrial Production.

The estimation proceeds by minimizing the asymmetric quantile loss:

$\hat{\beta}(\tau) = arg \min_{\beta} \sum_{t=1}^{T} \rho_\tau(r_t - X_t^T \beta)$, with the check loss as: $\rho_\tau(u) = u(\tau - 1\{u < 0\}.$

This loss function weights positive and negative residuals asymmetrically to take into account that, for example, a predictor may have little impact on average returns (τ = 0.50) but a strong effect during downturns (τ = 0.05) or expansions (τ = 0.95).

The quantile regression models are implemented in R using the `quantreg` package, which provides the standard Koenker–Bassett estimator. The conditional quantile functions are estimated over a big grid of quantiles τ = {0.05, 0.10, 0.25, 0.50, 0.75, 0.90, 0.95} in order to capture a wide range of market conditions. Quantiles like (0.05, 0.10, 0.90 and 0.95) aim to capture the most extreme negative and positive conditions which is the focus of this study, quantiles like 0.25 and 0.75 corresponds to moderate market conditions via which early warning signs could be deducted and finally the quantile at the median 0.5 is unaffected by the outliers and reflects the central tendencies.

In practice the model is fitted on R using the `rq()` function which solves the linear programming problem associated with the asymmetric check loss. For each quantile, R computes the coefficient vector$\hat{\beta}(\tau)$ and inference is carried out bootstrap-based standard errors, with the package's bootstrap option (se = "boot"), as recommended in the *quantreg* vignette and documentation, to account for the heavy-tailed nature of the return series.[2] Once the model is estimated, the coefficients are extracted and interpreted in terms of their effect on the corresponding conditional quantile of returns and their significance. Cross-quantile t-tests were also implemented and performed in order to assess whether slope coefficients are constant across the conditional return distribution by testing, for each regressor and pair of quantiles, the null $H_0: \beta_j(\tau_a) = \beta_j(\tau_b)$ via a Wald-type z-statistic and p-value, thereby enabling straightforward comparison of coefficient estimates across quantiles and market regimes.

3.3.3 Bayesian Quantile Regression

Bayesian Quantile Regression (BQR) is employed as a complementary approach where instead of giving a single estimate point in classical QR, it gives a whole distribution of plausible values of each coefficient. It requires a longer methodological process compared to the classical QR as it relies on the Bayesian framework where the estimation is based on two ingredients priors and the likelihood. A *prior* represents the initial belief about the possible values of a parameter before seeing the data, while the *posterior* is the updated distribution after observing the data. Formally, for each quantile level τ, the model specifies:

$$r_t = X_t^T \beta(\tau) + \varepsilon_{t,\tau'}$$

where X_t denotes the vector of predictors for month t, $\beta(\tau)$ is the vector of quantile-specific coefficients and $\varepsilon_t$is the error term with $\Pr(\varepsilon_{t,\tau} \leq 0 | x_t) = \tau$, and $\varepsilon_{t,\tau} \sim ALD(0, \sigma_\tau, \tau)$, where $\sigma_\tau$is the error scale.

3.3.3.1 ALD

The error term is assumed to follow an Asymmetric Laplace Distribution (ALD) (Benoit et al., 2017), which is a skewed distribution that is mathematically equivalent to the check-loss minimization function that define classical QR, by ensuring that the posterior mode of $\beta(\tau)$ corresponds to the classical Koenker–Bassett estimator. In fact, using an ALD error assumption in a regression model ensures that the τ-th quantile of the residuals is zero, aligning the model

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[2] https://search.r-project.org/CRAN/refmans/quantreg/html/predict.rq.html?utm_source=chatgpt.com

to target the τ-th conditional quantile of the response. So essentially the ALD connects the BQR to its quantile objective (Kozumi et al., 2009). In addition, an important note on the inclusion of the parameter σ in the ALD is the fact that it's treated as an unknown parameter to be estimated from the data and including it adds flexibility, allowing the model to adjust for the overall variability of returns at the given quantile (Kozumi et al., 2009).

Because there is a lack of strong prior beliefs about the magnitude or direction of each predictor's effect on stock returns, weakly informative priors were used for the model parameters. The goal is to let the data inform the posterior results while providing enough regularization to ensure stable estimation.

3.3.3.2 MCMC

With the model specified, Then the parameters' posterior distributions were estimated using Markov Chain Monte Carlo (MCMC) using Gibbs sampling algorithm implemented in the bayesQR package[3]. The MCMC were separately performed for each quantile (0.05, 0.10, …, 0.95), so each has its own chain of β samples amounting in seven quantile models estimated. After obtaining the MCMC samples, the posterior for each coefficient at each quantile were summarized by computing the posterior mean and 95% credible interval (using the 2.5th and 97.5th percentiles of the post-burn-in draws).

Overall, this Bayesian quantile regression set-up provides full posterior distributions for each coefficient $\beta(\tau)$ rather than just single values estimates, therefore it automatically offers credible intervals that quantify estimation uncertainty which is crucial in this study as the main focus is on the tails where data is naturally sparse, and estimates are inherently noisier. Regarding the later issue the Bayesian framework helps handling it as it also stabilizes inference through weakly informative priors. Combined with the ALD-based likelihood and MCMC estimation, the model remains flexible and robust while preserving the interpretability of the classical quantile regression framework. As a result, BQR enhances inference and interpretation in studies focusing on extreme market behavior and non-linear relationships, making it especially

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[3] https://crm.ugent.be/bayesQR_Benoit_VandenPoel_JSS_v76i07.pdf

suitable for tail-risk analysis in asset-return predictability (Yu & Moyeed, 2001; Kozumi & Kobayashi, 2011).

Concerning the interpretation of the results the Bayesian approach offers yet another inherent advantage where it allows for direct comparison of coefficient estimates across different quantiles and assesses the statistical significance of their differences. In this study, cross-quantile tests are to be conducted to examine whether a given predictor's effect at one quantile (say $\tau = 0.05$) is significantly different from its effect at another quantile (say $\tau = 0.95$).

3.3.4 Time-Varying Quantile Regression

When it comes to financial markets, the relationship between macro-financial variables and stock returns is likely to change across cycles and crises (e.g. dotcom, GFC, sovereign debt crisis, COVID, inflation shock, etc.). Therefore, in this study TVQR comes into play to relax the assumption that this relationship is time-invariant by estimating a coefficient surface $\beta_\tau(t)$ that evolves smoothly over time. Formally, for each quantile τ, the model can be written as:

$$Q_{r_t}(\tau|X_t) = X_t^T \beta(t;\tau)$$

where r_t denotes the STOXX 600 return at time t, X_t is the vector of standardized macro-financial predictors, and $\beta(t;\tau)$ is a vector of time-varying quantile coefficients. The coefficient vector $\beta_\tau(t_0)$ is obtained from Kernel-Weighted local quantile regression, using the quantreg package in R, around each evaluation time point t_0.

$$\hat{\beta}_\tau(t_0) = arg \min_{\beta} \textstyle\sum_{t=1}^{T} w_{t_0}(t)\, \rho_\tau(y_t - x_t^T \beta),$$

where $\rho_\tau()$ is the classical quantile (pinball) loss, and $w_{t_0}(t)$ are kernel weights that decrease the weights of observations further away from t_0 and observations that are closer to t_0 receive higher weights.

In short, the static BQR and classical QR performed earlier reveals how predictors affect the entire return distribution, but it implicitly assumes fixed relationships between variables over time. In contrast, TVQR allows the coefficients to evolve dynamically over time, which helps in addressing some econometric issues directly such as coefficient instability, this might happen when macro-financial conditions have time-varying predictive power. Another issue addressed is crisis sensitivity, where return–predictor relationship might suffer significant changes during events such as the dot-com crash, the 2008 crisis, the sovereign debt crisis, COVID-19, and the 2022 inflation shock. Thus, TVQR complements previous approaches (QR and BQR) by offering an additional dimension, hence modeling both the distributional (over quantiles) and the temporal (over time) dimensions.

4 Results & Discussion

4.1 Overview

This section evaluates whether macro-financial predictors contain information about monthly STOXX Europe 600 returns, and whether these relationships are stable and uniform across market states. It proceeds in a stepwise way from a mean-based benchmark to distribution- and time-sensitive frameworks. First, robust OLS is presented to provide an initial baseline and to illustrate what is learned when the analysis is restricted to the conditional mean. Second, static Quantile Regression (QR) examines heterogeneity across the return distribution, documenting how predictor effects differ between downside, normal, and upside market conditions; results are discussed predictor-by-predictor and complemented by a cross-quantile comparison to formally assess distributional asymmetry. Third, Time-Varying Quantile Regression (TVQR) extends this logic by allowing coefficients to evolve over time, highlighting how crises, regime shifts, and changing macro conditions reshape the return–predictor link within each quantile. Fourth, Bayesian Quantile Regression (BQR) is used as a robustness and uncertainty-aware counterpart, focusing on posterior credible intervals to evaluate how strongly the data support quantile-specific effects once parameter uncertainty is incorporated. Finally, the section revisits the hypotheses by synthesizing the cross-model evidence and linking the results to in-sample performance metrics (pinball loss and calibration), clarifying what type of predictability, if any, emerges, and under which parts of the distribution and time periods it is most pronounced.

4.2 OLS (HC1)

The OLS estimates provide an initial benchmark for understanding the drivers of STOXX 600 returns, but they reveal only part of the underlying dynamics. The regression identifies only volatility as significant predictor which exerts a strong and negative influence in line with theories linking uncertainty to higher risk premia and weaker valuations. Using heteroskedasticity-robust (HC1) standard errors, volatility is strongly significant ($\beta = -0.0137$, $t = -5.67$, $p < 0.0001$), confirming a statistically robust negative average effect in the mean-based model. In contrast, the remaining macroeconomic variables appear insignificant in this mean-based specification. More precisely, most coefficients are statistically indistinguishable from zero (term spread: $\beta = -0.0036$, $p = 0.133$; industrial production: $\beta = 0.0003$, $p = 0.89$), while inflation and oil prices are only marginally significant at the 10% level (inflation: $\beta = -0.0039$, $p = 0.085$; oil prices: $\beta = 0.0043$, $p = 0.07$). (see Figure 12). Taken at face value, these results could suggest that macroeconomic fundamentals contribute little to monthly equity return variation. However, such an interpretation overlooks a key limitation of OLS that is estimating a single average effect across the entire distribution of returns, which implicitly assumes that predictors operate identically in periods of stress, stability, and expansion. As shown by Cenesizoglu and Timmermann (2008), averaging over heterogeneous market conditions can wash out tail-specific effects, making variables that matter during downturns or booms appear irrelevant in the mean.

Therefore, the muted OLS coefficients should not be interpreted as evidence of economic irrelevance, but rather as an indication that the relationships between predictors and returns may be asymmetric or state-dependent. This insight motivates the use of quantile regression, as it has already been stated, which allows these effects to vary across the return distribution and provides a more comprehensive view of how macro-financial conditions shape market outcomes under different regimes.

4.3 Quantile regression[4]

4.3.1 Volatility (VSTOXX)

Volatility, proxied by the VSTOXX index, emerges as one of the strongest and most asymmetric predictors across the entire return distribution. In the lower quantiles, the coefficients are large, negative, and highly significant (e.g., -0.03 at $\tau = 0.05$, -0.029 at $\tau = 0.10$, and -0.024 at $\tau = 0.25$) (see Figure 13 & Figure 14 & Figure 15) with a p-value well below

[4] Refer to the heatmap in Figure 20 to get an overview of the significatively of each coefficient across quantiles.

1%, indicating that increases in implied volatility substantially intensify downside risk. Around the median (τ = 0.50) (see Figure 16), volatility remains negative and statistically significant, though with a reduced magnitude suggesting that elevated uncertainty dampens typical market performance as well. This pattern is fully consistent with the well-established countercyclical nature of volatility documented by Schwert (1989) and Campbell and Hentschel (1992), who show that volatility spikes during recessions and market stress which are precisely the conditions captured in the left tail of the return distribution.

At higher quantiles, however, the relationship reverses sign as volatility becomes positively associated with returns and remains significant in the extreme right tail (e.g., +0.014 at τ = 0.90 and +0.021 at τ = 0.95) (see Figure 18 & Figure 19). This latter pattern hasn't been consistently detected in famous empirical studies. Still, one could speculate that the sign reversal may stem from the mechanism uncovered by Altinkeski et al. (2024), who showed that during extreme market conditions, either crashes or rallies, the volatility index in, in their case "VIX", is not just a barometer but can itself be influenced by the stock market. In other words, instead of the VIX always driving equities, there are moments when the relationship flips. Similarly, this dynamic could explain why extreme return shocks might spill over into the VSTOXX index and trigger the heightened volatility captured in the upper quantiles (90% and 95%) of the QR model. This studies' results are also consistent with evidence from a study conducted by Aslanidis et al. (2021), which highlights that the risk–return trade-off is not linear; risk (measured by the VIX) is negatively related to returns in the lower tail but positively associated in the upper tail, suggesting a conditional and asymmetric relationship rather than a constant premium for risk.

Overall, volatility exhibits a distinctly nonlinear and distribution-dependent influence, where it becomes strongly negative during periods of market stress, mildly negative in normal conditions, and positive during potential rebound phases, underscoring why quantile regression is essential for capturing the full complexity of its predictive role

4.3.2 Term Spread

The first-difference of the term spread exhibits a predominantly negative association with STOXX 600 returns across the quantiles. The series itself is highly stationary and characterized by infrequent but pronounced spikes, most notably during the 2008–2009 financial crisis, the euro-area and the post COVID-19 period 2022-2023, indicating that the variable reflects abrupt policy adjustments, risk-off episodes, or market re-pricing rather than gradual macroeconomic trends. In the quantile regression results, the term-spread shock variable is insignificant in the lowera and extreme lower tail and around the median, implying that changes in the term spread do not systematically amplify equity crashes or affect typical market conditions. However, the coefficient becomes significant and increasingly negative in the upper tail and $\tau = 0.95$ (see Figure 19), indicating that sharp upward movements in the term spread tend to limit the upside during exceptionally strong months.

4.3.3 Oil Prices

Across the conditional distribution, oil prices exhibit a small, positive association with STOXX Europe 600 log-returns, but this relationship is generally not statistically significant. With the exception of the extreme lower tail ($\tau = 0.05$), where the coefficient becomes significant ($\beta \approx 0.0116$, $p \approx 0.017$), the estimated effects remain modest in magnitude and fail to reach conventional significance levels at the median and upper quantiles (up to $\tau = 0.95$). This pattern suggests that monthly oil-price movements have limited predictive value overall, with any detectable signal concentrated in severe downturn states rather than in normal or strong market conditions.

4.3.4 Inflation

Inflation shows a clear asymmetric relationship with STOXX Europe 600 monthly returns. The coefficients are negative across most quantiles and become statistically significant in the lower tail, indicating that higher inflation is mainly associated with weaker returns during downside market conditions rather than across the full distribution. In particular, the quantile regression estimates are significant at $\tau = 0.05$ with a p value of 0.02 and remain significant at $\tau = 0.10$ and $\tau = 0.25$, with the strongest evidence at $\tau = 0.25$. Beyond these lower quantiles, inflation does not appear to have a robust effect at conventional levels of significance (see Figure 13 & Figure 15). These findings are consistent with long-standing empirical evidence showing a negative relationship between inflation and stock returns (Fama & Schwert, 1977; Gultekin, 1983; Barnes et al., 1999).

By contrast, inflation becomes statistically irrelevant at the median and across the upper quantiles ($\tau \geq 0.50$). This suggests that inflation does not influence typical or positive market conditions. The asymmetric nature of the relationship echoes Fama's (1981) "proxy hypothesis", where inflation proxies for weaker economic conditions, and with the mispricing channel of Modigliani & Cohn (1979), in which inflation-induced valuation errors intensify particularly during stressed market conditions.

Taken together, the results indicate that inflation is not a general predictor of equity returns but rather a state-dependent and tail-specific variable, exerting influence only when the market is already vulnerable or in extreme downturns. This reinforces the view, echoed in Boucher (2006) and related literature, that inflation captures macro-financial stress conditions whose effects materialize asymmetrically, becoming economically relevant only during episodes of heightened downside risk.

4.3.5 Industrial Production

Industrial production shows no meaningful predictive power for STOXX 600 log-returns across the entire return distribution. The estimated coefficients remain extremely small even negative at all quantiles and never achieve statistical significance. For example, at the lower tail, the coefficient is, then becomes weakly positive around the 0.25 and 0.5 quantiles and reverts to small negative values in the upper parts of the distribution. These values remain economically negligible and statistically insignificant throughout, indicating that fluctuations in real economic activity do not materially shape either the downside, median, or upside behavior of monthly European equity returns. The insignificance persists even in the lower tail, where macroeconomic variables sometimes exhibit stronger effects, reinforcing the conclusion that industrial production does not provide additional information about periods of market stress.

This empirical pattern aligns with some literature documenting the weak short-horizon predictive content of real activity indicators. Schwert (1989) shows that industrial production growth is largely disconnected from short-term return variations. Cenesizoglu and Timmermann (2008) further demonstrate that many macroeconomic predictors lose statistical significance across different parts of the return distribution, particularly at higher sampling frequencies.

Overall, the quantile regression estimates provide coherent evidence that industrial production, despite its central role in business cycle analysis, does not meaningfully inform short-term return dynamics at any point of the distribution.

4.3.6 Cross Quantiles Evidence

A central premise of this section is that the relationship between macro-financial predictors and equity returns is unlikely to be uniform across market states. While ordinary least squares (OLS) focuses exclusively on the conditional mean, the cross-quantile comparison results (see Figure 22) and the visual patterns from the coefficient-by-quantile plot (see Figure 21) both indicate substantial heterogeneity across the return distribution. For several predictors, the estimated effects vary noticeably between lower, central, and upper quantiles, revealing asymmetries that a linear mean model cannot capture. If a standard linear specification were adequate, the QR coefficient profiles would be nearly flat and the cross-quantile differences insignificant. Instead, both the statistical tests and the graphical evidence show clear distributional shifts, with some variables exerting stronger influence in downturns and others becoming relevant only during high-return episodes. These features justify reinforcing the need to explore frameworks beyond being mean-based and motivate the use of Quantile Regression, which allows a more complete characterization of how predictors behave across the entire range of STOXX 600 returns.

4.4 Time-Varying Quantile Regression

4.4.1 Volatility (VSTOXX)

Volatility displays the clearest and most persistent structure in the TVQR results (see Figure 23). Coefficients are consistently negative in the lower quantiles, especially during major market stress episodes such as the dot-com downturn, the 2008 financial crisis, and the COVID shock. This indicates that rising volatility systematically worsens downside equity outcomes. In contrast, coefficients become consistently positive in the upper quantiles, particularly from 2010 onward, suggesting that in strong market regimes, volatility accompanies higher upside potential. This stable cross-quantile asymmetry highlights volatility as a state-dependent risk variable, as it depresses left-tail returns while contributing positively to right-tail outcomes. These findings are fully consistent with the static QR estimates, which show the same sign asymmetry across quantiles; however, the TVQR framework adds an important layer by revealing how the strength of these effects evolves across crises and expansions. In other words, while QR captures the average asymmetric relationship between volatility and returns, TVQR uncovers its time-varying nature, offering a clearer and more nuanced understanding of how volatility influences equity performance under different market conditions.

4.4.2 Term Spread

In the early 2000s the coefficients of the term spread at all quantiles fluctuate tightly around zero (see Figure 23), indicating a weak and broadly symmetric association between the term spread and stock returns. Around the global financial crisis, the coefficients for lower and upper quantiles become more negative than those at the median, suggesting that changes in the term spread affect both downside risk, and extreme gains. The relationship weakens again in the immediate post-crisis period, before a pronounced positive hump emerges between 2015 and 2017, when a steeper curve is strongly associated with higher 5th and 10th percentile returns, consistent with a reduction in left-tail risk. From 2018 onwards, the coefficients turn persistently negative across virtually all quantiles, with particularly large magnitudes around the 25th and 50th percentiles, implying that in this regime a steeper term structure is systematically linked to lower typical and mildly adverse stock returns. These patterns underline both the time variation and the strong distributional heterogeneity in the predictive content of the term spread for European equity returns.

Taken together, these TVQR patterns are broadly consistent with the static QR evidence. In both frameworks, term-spread shocks are, on average, associated with a predominantly negative effect on returns, with the strongest and most significant impacts appearing in extreme upper part of the distribution rather than in the lower tail or at the median. However, the TVQR results refine this picture by showing that the magnitude and at times even the direction of the term-spread effect changes depending on the market environment. For example, the positive hump of the extreme lower quantiles observed around 2015–2017 contrasts sharply with the long post-2018 period during which coefficients become persistently and uniformly negative across nearly all quantiles. TVQR also reveals that during the 2008 financial crisis, both the lower and upper quantiles exhibit a much more pronounced negative impact compared with the years immediately before and after the crisis. This non-linearity within each quantile is averaged out, by construction, in the QR framework. In this sense, QR captures the overall distributional pattern of the term spread, whereas TVQR exposes how this relationship evolves across different market regimes and highlights the specific episodes that shape its predictive power for European equity returns.

4.4.3 Oil Prices

Oil-price coefficients show a strong and economically meaningful sign reversal across time. in the late 1990s and early 2000s, the quantile coefficients do not follow a clear common pattern as shown on (see Figure 23) the lower quantiles display a strong negative relationship with stock returns, whereas the upper quantiles are initially positive but quickly decline toward zero or slightly negative values around 2000. This divergence might be due to when Brent crude tripled from about $9 to over $30 per barrel after OPEC cut production and East Asian demand rebounded indicating that rising oil prices were associated with weaker equity outcomes. Around 2001 the coefficients started moving upwards, crossing zero around 2009 and remaining positive for nearly a decade across most quantiles. The positive effect weakens slightly and flattens towards the end of the sample, more precisely from 2019 onwards but remains above zero, this mirrors evidence that the oil–stock link in Europe became time-varying after the early 2000s.

As a reminder, the static quantile regression delivers small, positive oil price coefficients, with statistical significance only at the lowest quantile. The TVQR results are consistent with that broad message in terms of typical magnitude, since the coefficients spend substantial time close to zero, but they also show that the effect is strongly time varying in both sign and size. In the early part of the sample, the oil price coefficient is often negative in the lower quantiles, then it turns positive around the late 2000s and becomes more pronounced through much of the 2010s, especially for the lower and middle quantiles, before drifting back toward zero again in more recent years. Once these regime dependent movements are averaged within each quantile over the full period, positive and negative episodes partially offset each other, which helps explain why the static QR collapses to small effects with limited significance.

4.4.4 Inflation

The effect of inflation fluctuates markedly across time and market regimes. In the lower quantiles, inflation begins in the late 1990s and early 2000s with strongly negative coefficients most pronounced in the 5th and 10th percentiles, indicating that inflation pressures disproportionately worsen downside returns (see Figure 23). These effects weaken substantially during the mid-2000s expansion, intensify again during the 2008–2009 financial crisis, and then gradually diminish as coefficients converge toward zero throughout the 2010s low-inflation environment. Upper quantiles follow the same general pattern but with milder movements around zero, particularly during stable periods when inflation loses much of its explanatory power. By the end of the sample, all quantiles cluster close to zero, highlighting a structural decline in the inflation–return link.

While the static QR shows that inflation has a modest to strong negative effect in the lower tail TVQR reveals that this impact is highly regime dependent. Inflation strongly worsens downside returns during crisis periods but is largely negligible in stable regimes, so its pronounced negative episodes average out in the static model, making the overall effect appear weaker than it actually is over time.

4.4.5 Industrial Production

Industrial production shows only a mild and unstable relationship with STOXX 600 returns, with coefficients that fluctuate around zero across quantiles and time (see Figure 23). In the early part of the sample (late 1990s to early 2000s), IP displays small positive values in the upper quantiles and mildly negative or near-zero effects in the lower quantiles, suggesting that real activity exerted only a weak influence on returns and did so asymmetrically. As the sample progresses toward the mid-2000s, all quantiles drift toward zero, reflecting a period where changes in industrial production provided little information about either downside or upside market movements.

A notable pattern emerges during the 2008–2009 financial crisis, where the lower quantiles (especially $\tau = 0.05$) experience a sharp drop into significantly negative territory. This indicates that contractions in industrial production were associated with disproportionately worse left-tail equity outcomes during periods of severe economic stress. Upper quantiles, meanwhile, also turn mildly negative but to a much lesser extent, showing that real economic deterioration was not only a recession signal but one that disproportionately affected downside returns.

After 2010, the relationship weakens considerably across all quantiles. The coefficients converge tightly around zero and remain remarkably flat through the 2010s and early 2020s, illustrating that industrial production lost almost all predictive relevance for monthly European equity returns during this stable, low-growth regime.

Overall, both QR and TVQR point to the same conclusion: industrial production has limited predictive power for European stock returns, with effects that are generally small, short-lived, and largely confined to recessionary episodes particularly in the left tail during major downturns.

4.5 Bayesian Quantile regression

The Bayesian quantile regression (BQR) results show that for each estimated quantile, the posterior credible intervals for all predictors span zero. This is a critical finding because, unlike classical quantile regression, BQR does not just deliver a point estimate and an asymptotic standard error; instead, it yields an entire posterior distribution for each coefficient. When the 90 % credible interval for a parameter contains zero, it means that, given the data and the prior assumptions, there is no high-probability evidence that the true effect is strictly positive or negative at that quantile. (see Figure 24 & Figure 25 & Figure 26)

Looking at the R output, this pattern holds across the full distribution. For example, at $\tau = 0.05$ the posterior mean for volatility is around –0.09 with a credible interval roughly from –0.28 to +0.06. Similar wide, zero-spanning intervals appear for term spread, industrial production, inflation and oil prices. Even when the standard QR and TVQR models suggested a positive coefficient for a certain variable, the Bayesian estimates come with credible intervals that include both substantial positive and negative values. This means the Bayesian framework is acknowledging that, once parameter and model uncertainty are accounted for, the data are consistent with a range of possible effects including no effect at all.

The cross-quantile tests show no significant difference of the predictors impact in returns across t(he whole set of quantiles apart from the intercept (see Figure 27)

This systematic inclusion of zero within the credible intervals suggests that, once parameter and sampling uncertainty are accounted for, the evidence for a stable and statistically credible impact of these predictors on STOXX 600 returns weakens considerably. The broader credible bands likely reflect a combination of factors, including limited sample size, time variation in relationships, heavy-tailed return distributions, and potential model misspecification. In this sense, BQR acts as a robustness check on the classical models, highlighting that some of the effects interpreted as significant in QR or persistent in TVQR may be sensitive to estimation assumptions. This does not mean the variables have no economic relevance, but it does highlight the importance of considering parameter uncertainty and the risk of over-interpreting point estimates in small or noisy samples.

4.6 Revisiting the Hypothesizes.

4.6.1 The impact of variables on stock returns is non-linear and pronounced in the extremes

“Does the impact of macro-financial variables change across extreme quantiles, and if yes, to what extent?”

The results of this study provide strong evidence that the impact of macro-financial variables on European stock returns is not constant across the return distribution. Both the static quantile regression (QR) and the time-varying quantile regression (TVQR) models reveal clear asymmetries in how predictors influence the whole distribution of the returns of the STOXX 600 index, depending on market conditions represented by different quantiles. Volatility, for instance, exerts a significantly negative effect in the lower quantiles, indicating that heightened uncertainty intensifies downside risk, but reverses sign in the upper tail, where it becomes positively associated with strong returns. Inflation shows its most meaningful and statistically significant influence in the lower part of the distribution, particularly at $\tau = 0.25$, while its effect fades near the median and becomes negligible in the upper quantiles. Similarly, the term spread exhibits increasingly negative effects as we move toward the tails, especially in more recent periods. Oil prices are only tail-relevant in the extreme downside in QR ($\tau = 0.05$), while TVQR indicates a regime-dependent effect that shifts over time rather than remaining stable across quantiles. In contrast, industrial production demonstrates consistently weak and statistically insignificant effects across the entire distribution, suggesting limited explanatory power in both normal and extreme market regimes.

Taken together, these findings partially support the hypothesis that macro-financial predictors exert heterogeneous effects across the STOXX 600 return distribution with a stronger impact and higher significance at the extremes, although not uniformly across models. The patterns are most evident in QR and TVQR, where they emerge as economically plausible and time-sensitive relationships. However, these effects lose statistical robustness once parameter uncertainty is fully incorporated. The Bayesian quantile regression (BQR) yields wide posterior intervals that include zero for all slope coefficients at every quantile. This suggests that, conditional on the data, the evidence for stable, quantile-specific macro-financial effects is too weak to withstand a rigorous probabilistic treatment. The divergence between QR and BQR thus highlights that any predictive signals identified in classical models are fragile and may be easily diluted by estimation noise at the monthly frequency. While QR and TVQR point to conditional and asymmetric dynamics in macro–return linkages, BQR calls for a more cautious interpretation, emphasizing the uncertainty that underlies these relationships and the importance of not overstating their robustness.

4.6.2 Time varying model performs better than static models

"Which model performs better in-sample?"

The second hypothesis which suggest that coefficient dynamics improves model fit is strongly supported. Across all quantiles, the time-varying quantile regression (TVQR) produces the *lowest* in-sample pinball loss and the *best* quantile calibration, confirming that it delivers the most accurate conditional quantile forecasts. For example, at the 5% quantile, the TVQR pinball loss is only 0.003, compared with 0.0037 for classical QR and 0.015 for BQR (see Figure 28 & Figure 29 & Figure 30); similarly, at the median, TVQR achieves 0.0138 versus 0.0151 (QR) and 0.0152 (BQR). The hit rates (see Figure 31) further confirm the superior calibration of TVQR: coverage is almost perfectly aligned with the theoretical quantiles (e.g., 0.078 for $\tau = 0.05$ and 0.96 for $\tau = 0.95$), whereas QR deviates more substantially (see Figure 28). The Bayesian QR (BQR) performs worst in terms of pinball loss at every quantile (e.g., 0.0149–0.0160 across the entire τ range), reflecting the fact that posterior shrinkage induces strong parameter smoothing. While this stabilizes estimates, it also causes the model to systematically underreact to time-variation in the data, generating quantile forecasts that are overly conservative and therefore incur higher quantile loss

By allowing coefficients to evolve smoothly over time, TVQR captures regime-dependent structure that static models fundamentally miss. Periods of volatility spikes, inflationary bursts, and commodity-price cycles all generate visible shifts in the estimated β (t, τ), particularly at the tails, where downside risk and upside recoveries are most sensitive to macro-financial conditions. These time-varying adjustments translate into notably improved forecasts, especially during crisis periods such as the dot-com crash, the 2008 GFC, the euro-area debt crisis, and the 2020 COVID shock, when the conditional distribution of returns experiences abrupt transitions. Cenesizoglu and Timmermann (2008) argue that modeling stock returns through a time-varying conditional distribution improves the characterization of tail behavior and reduces the sensitivity of return forecasts to unexpected extreme observations. The static QR, while able to detect cross-sectional average effects across quantiles, cannot adapt to structural breaks or evolving macroeconomic regimes. Its coefficients are fixed, limiting its ability to accommodate changes in risk perception, monetary cycles, or shifts in investor sentiment.

In sum, the combined evidence suggests that any macro-financial predictability present in monthly STOXX 600 returns is weak on average (OLS), weak, stable, distribution-invariant predictability (BQR), detectable in static cross-quantile structure (QR), but ultimately driven by time-varying and regime-specific dynamics (TVQR). The superior performance of the time-varying model validates the hypothesis that the return–predictor relationships are not stable constants, but evolving functions shaped by market cycles, crises, and changing macroeconomic conditions. Static models, particularly the Bayesian one, struggle to reconcile these shifts and thus deliver inferior in-sample performance. The revised conclusion is therefore that predictability exists, but only in a temporally adaptive form.

5 Limitation and Future Research

This study offers important insights into the conditional and time-varying effects of macro-financial variables on European equity returns using the STOXX 600 index. However, several limitations should be acknowledged. First, the analysis was restricted to a single market index "STOXX 600" which may limit the generalizability of the findings to other regional or asset-specific equity indices. Future research could examine whether similar patterns hold across national markets or sectoral indices within Europe.

Second, although the Bayesian quantile regression (BQR) used in this study provides valuable insights into parameter uncertainty and allows for flexible estimation under relaxed distributional assumptions, it produced wide credible intervals that systematically encompassed zero. This suggests that, especially at the monthly frequency, the signal-to-noise ratio may be too low for strong predictive inference. Longer samples with more data points or higher-frequency observations may allow for tighter posterior estimates and more robust conclusions.

Third, even though the variable set used is based on macro-financial theory, it might leave out important predictors like sentiment indices, liquidity conditions, or global spillovers. To better capture the intricacy of equity return dynamics, future research could include a larger variety of predictors.

Lastly, while time-varying quantile regression (TVQR) outperformed static models in capturing changing relationships over time, future work could focus on evaluating model performance in out-of-sample settings, assessing whether these patterns translate into forecasting gains. Dangl and Halling (2012), showed in their study promising out-of-sample performance of predictive models when time-varying coefficients were allocated, however the study was done on the S&P 500 index in the U.S. stock market.

In sum, future research should consider expanding both the data scope (markets, predictors, sample length) and the evaluation approach (e.g., forecast accuracy) to build a more comprehensive understanding of macro-financial predictability in European equities.

6 Conclusion

This study set out to investigate whether macro-financial variables can predict monthly European equity returns, with a particular focus on the conditional distribution of returns and the potential asymmetries and time variation in predictor effects. Using the STOXX Europe 600 index as the benchmark for European stock market performance, the analysis incorporated a wide set of explanatory variables including implied volatility (VSTOXX), inflation, term spread, industrial production, and oil prices,to test for predictive power across different market states and economic regimes.

To fully explore these relationships, the study implemented a range of econometric techniques, beginning with ordinary least squares (OLS) as a baseline, followed by classical quantile regression (QR), time-varying quantile regression (TVQR), and Bayesian quantile regression (BQR). Each model was chosen to reveal distinct aspects of the return–predictor relationship: OLS captures average effects; QR uncovers distributional asymmetries; TVQR allows for both distributional and temporal dynamics; and BQR introduces probabilistic rigor by accounting for estimation uncertainty.

The findings provide strong support for the idea that the influence of macro-financial variables on stock returns is asymmetric and conditional. Volatility emerges as the most robust and state-dependent predictor, negatively associated with downside returns but positively linked to upper-tail outcomes, a dynamic that QR and TVQR both confirm. Term spread and inflation also show quantile-dependent effects, particularly in the lower tail, while oil prices and industrial production exert weaker, statistically insignificant influence across most quantiles. However, the Bayesian QR results reveal that when full parameter uncertainty is incorporated all credible intervals contain zero, suggesting that the observed relationships are not statistically robust in a probabilistic sense and may be fragile in small or noisy samples.

The model comparison confirms the second hypothesis: that allowing coefficients to evolve over time improves model fit. TVQR consistently outperforms both static QR and BQR in terms of in-sample pinball loss and quantile calibration. It is the only framework capable of capturing regime shifts during major economic events such as the dot-com bubble, the global financial crisis, the European sovereign debt crisis, and the COVID-19 shock, meaning when the return–predictor dynamics undergo substantial changes. This superior performance highlights that any existing predictability is not stable over time but arises from evolving macroeconomic environments and structural breaks.

In sum, the results suggest that:

- Average macro-financial predictability is weak (OLS).
- Statistically robust predictability is fragile (BQR).
- Predictability is detectable in cross-quantile patterns (QR).
- But true, economically meaningful predictability is time-varying and regime-specific (TVQR).

Thus, the revised conclusion is that stock return predictability in European markets exists, but only in a temporally adaptive form, one that is sensitive to shifts in macro-financial conditions and market regimes. Static models, particularly BQR, fail to capture these shifts and therefore underperform. Quantile-based, time-varying approaches offer a more accurate and nuanced understanding of how macroeconomic forces shape financial returns under different states of the world.

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8 Appendixes

8.1 Tables & Figures

Table 1: Correlation matrix

	returns	*inflation*	*term_spread*	*industrial_production*	*volatility*	*oil_prices*
returns		-0.087	-0.128*	0.015	-0.354***	0.168**
inflation	-0.087		-0.092	-0.022	0.008	-0.017
term_spread	-0.128*	-0.092		-0.011	0.201***	0.087
industrial_production	0.015	-0.022	-0.011		-0.004	0.034
volatility	-0.354***	0.008	0.201***	-0.004		-0.238***
oil_prices	0.168**	-0.017	0.087	0.034	-0.238***	

Computed correlation used pearson-method with listwise-deletion.

Figure 1: Correlation Heatmap

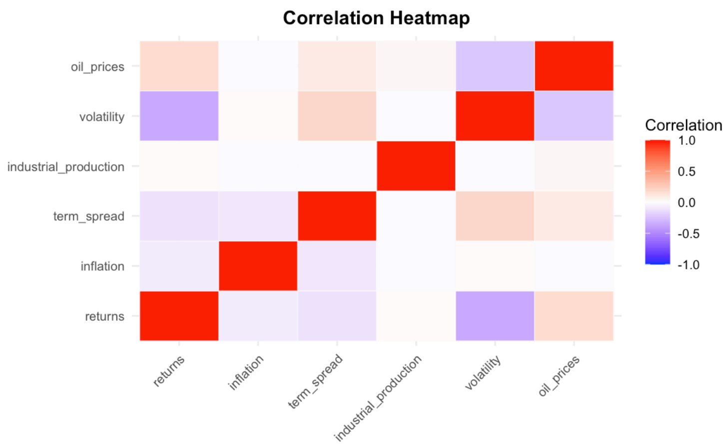


Table 2: VIF Diagnostics

Variance Inflation Factors

Variable	*VIF*
inflation	1.010
term_spread	1.074
industrial_production	1.002
volatility	1.120
oil_prices	1.083

Table 3: Heteroskedasticity & Normality Diagnostics

Normality Diagnostics for Returns

Statistic	*Value*
Jarque–Bera	46.7519
P-value	0
Skewness	-0.6461
Kurtosis	4.3592
Excess Kurtosis	1.3592
Conclusion	Non-normal distribution (reject normality)

Figure 2: Skewness-Kurtosis Reference Plots

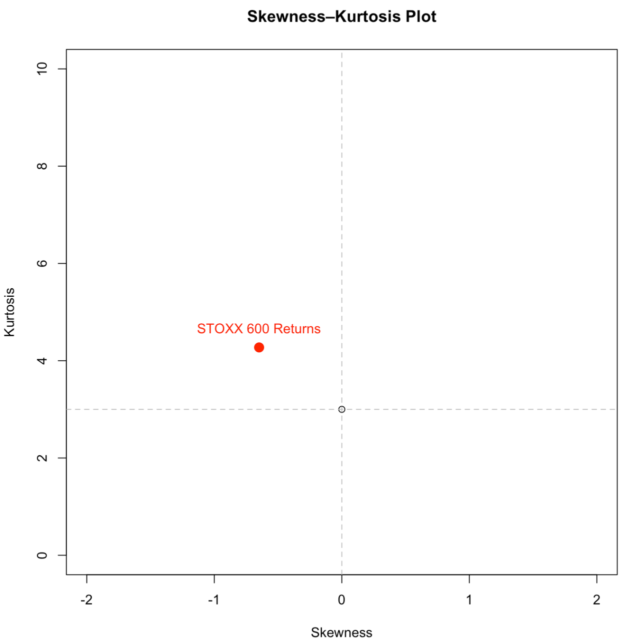


Figure 3: Q-Q Plot of STOXX 600 Returns

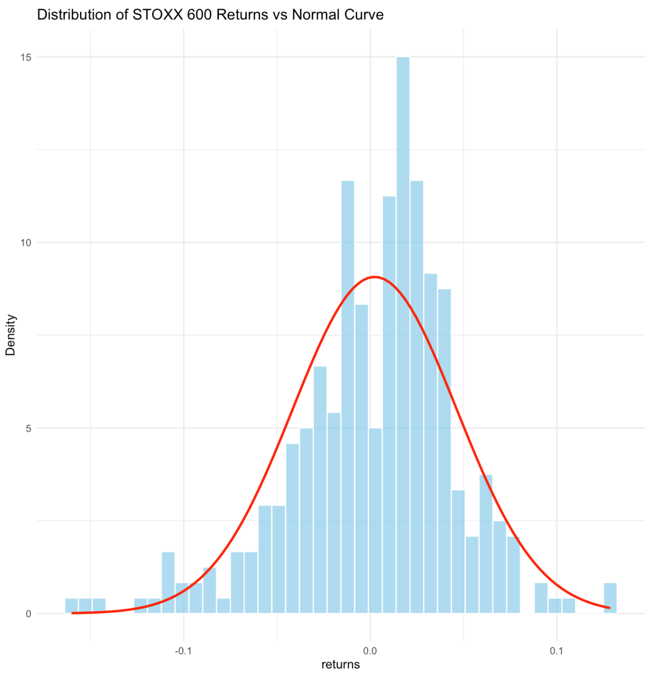


Figure 4: Distribution Plot of STOXX 600 Returns

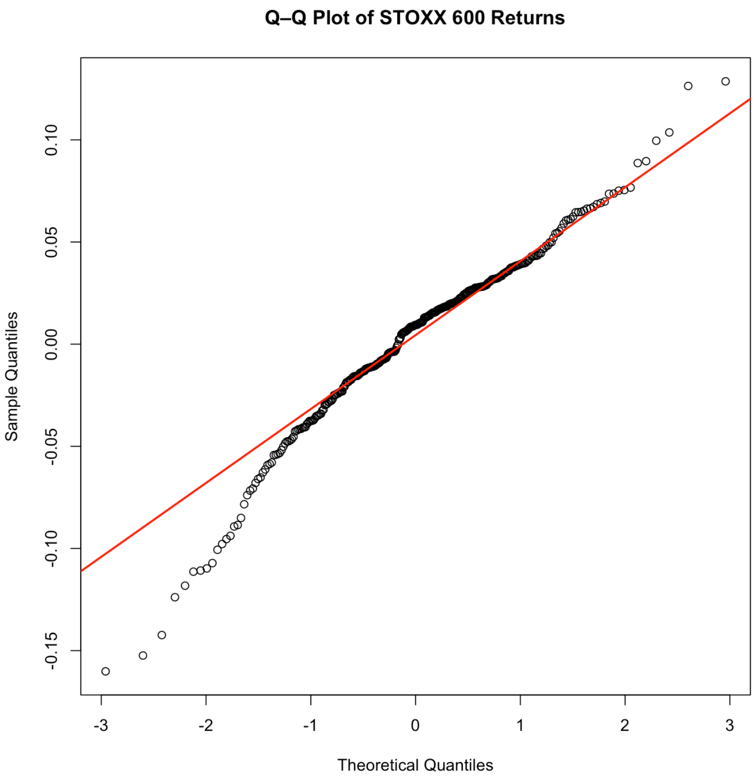


Figure 5: STOXX 600 Return Timeseries Plot

Figure 6: Term Spread Timeseries Plot

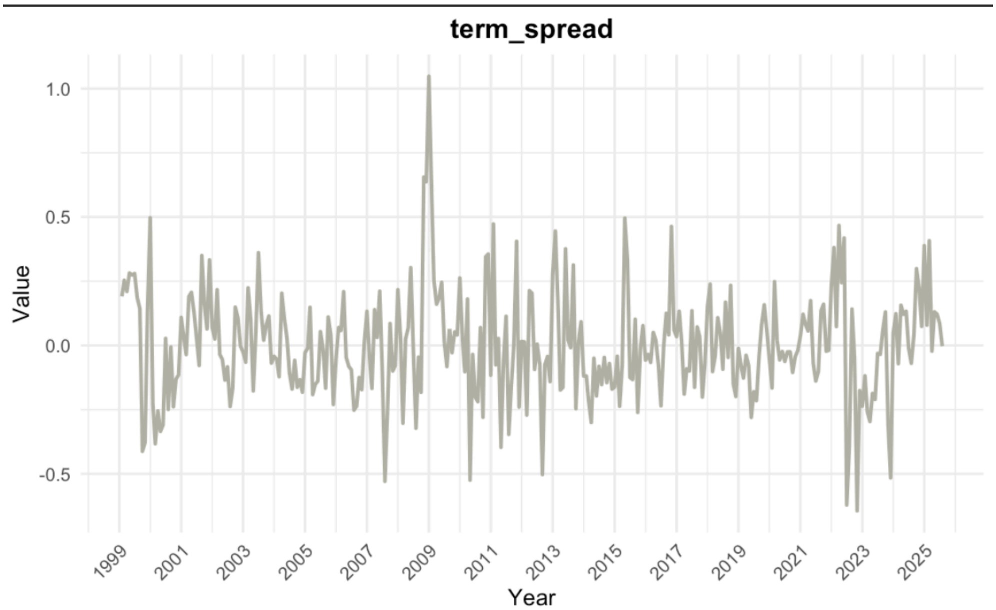


Figure 7:Oil Prices Timeseries plot

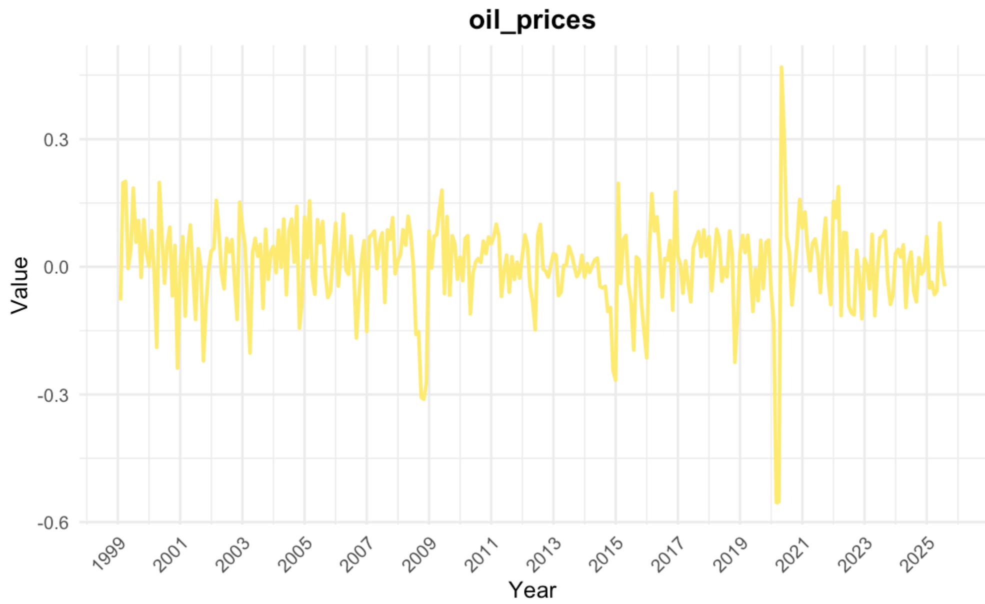


Figure 8: Industrial Production Timeseries Plot

Figure 9: Inflation Timeseries Plot

Figure 10: Volatility (VSTOXX) Timeseries Plot

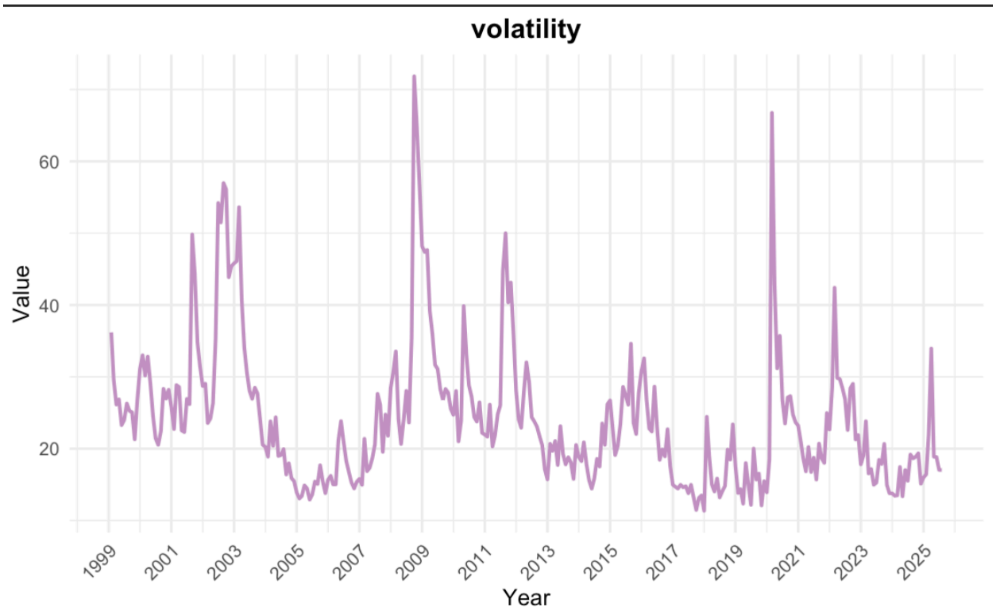


Figure 11: OLS & OLS HC1 Resgressions Output

OLS Coefficients (Classical vs HC1 Robust SE)

term	estimate	std_error	statistic	p_value	std_error_hc1	t_value_hc1	p_value_hc1	sig_hc1
(Intercept)	0.0021	0.0023	0.9023	0.3676	0.0023	0.9023	0.3676	
volatility	-0.0137	0.0024	-5.6740	0.0000	0.0034	-3.9940	0.0001	***
term_spread	-0.0036	0.0024	-1.5060	0.1331	0.0024	-1.4846	0.1387	
oil_prices	0.0043	0.0024	1.8160	0.0703	0.0031	1.3706	0.1715	
inflation	-0.0039	0.0023	-1.7256	0.0854	0.0028	-1.4183	0.1571	
industrial_production	0.0003	0.0023	0.1347	0.8929	0.0022	0.1415	0.8875	

Figure 12: OLS Regression statistics

OLS Model Fit Statistics

n	df_model	df_resid	r_squared	adj_r_squared	sigma	f_stat	f_p_value
319	5	313	0.1461	0.1325	0.0406	10.7142	0

Figure 13 : QR Results at 5% Quantile

Quantile Regression Results (τ = 0.05)

Quantile	Variable	Coefficient	Std. Error	P-value	Signif
0.05	(Intercept)	−0.055727179	0.004368576	0.000000	***
0.05	volatility	−0.031532518	0.003204669	0.000000	***
0.05	term_spread	−0.000116494	0.005462949	9.830005×10^{-1}	
0.05	oil_prices	0.011560397	0.004831710	1.731834×10^{-2}	*
0.05	inflation	−0.011656248	0.005085280	2.256016×10^{-2}	*
0.05	industrial_production	−0.002317915	0.004430026	6.011855×10^{-1}	

Note: *** p<0.001, ** p<0.01, * p<0.05

Figure 14: QR Results at 10% Quantile

Quantile Regression Results (τ = 0.10)

Quantile	Variable	Coefficient	Std. Error	P-value	Signif
0.10	(Intercept)	−0.045068589	0.003669306	0.000000	***
0.10	volatility	−0.028582905	0.003624060	5.218048×10^{-14}	***
0.10	term_spread	−0.000556939	0.003673983	8.796079×10^{-1}	
0.10	oil_prices	0.007075923	0.004673359	1.310102×10^{-1}	
0.10	inflation	−0.007460217	0.003496634	3.365756×10^{-2}	*
0.10	industrial_production	−0.000562657	0.003612605	8.763319×10^{-1}	

Note: *** p<0.001, ** p<0.01, * p<0.05

Figure 15: QR Results at 25% Quantile

Quantile Regression Results (τ = 0.25)

Quantile	Variable	Coefficient	Std. Error	P-value	Signif
0.25	(Intercept)	−0.025625245	0.002681950	0.000000	***
0.25	volatility	−0.024717295	0.003877911	6.593746×10^{-10}	***
0.25	term_spread	−0.005868887	0.003148487	6.325295×10^{-2}	
0.25	oil_prices	0.005034929	0.003659010	1.697943×10^{-1}	
0.25	inflation	−0.007729131	0.003218017	1.689582×10^{-2}	*
0.25	industrial_production	0.001543501	0.003844024	6.883021×10^{-1}	

Note: *** p<0.001, ** p<0.01, * p<0.05

Figure 16: QR Results at 50% Quantile

Quantile Regression Results (τ = 0.50)					
Quantile	Variable	Coefficient	Std. Error	P-value	Signif
0.50	(Intercept)	0.004410743	0.003345111	1.882788×10^{-1}	
0.50	volatility	−0.015591677	0.004404398	4.608281×10^{-4}	***
0.50	term_spread	−0.001240301	0.003522201	7.249716×10^{-1}	
0.50	oil_prices	0.003186214	0.003789488	4.011000×10^{-1}	
0.50	inflation	−0.003601935	0.003937081	3.609618×10^{-1}	
0.50	industrial_production	−0.000288123	0.003193981	9.281796×10^{-1}	
Note: *** p<0.001, ** p<0.01, * p<0.05					

Figure 17: QR Results at 75% Quantile

Quantile Regression Results (τ = 0.75)					
Quantile	Variable	Coefficient	Std. Error	P-value	Signif
0.75	(Intercept)	0.026101692	0.004488372	1.492645×10^{-8}	***
0.75	volatility	−0.004482916	0.005497458	4.154334×10^{-1}	
0.75	term_spread	−0.005361197	0.003091600	8.388193×10^{-2}	
0.75	oil_prices	0.002524637	0.003647358	4.893359×10^{-1}	
0.75	inflation	−0.003918611	0.004446760	3.788704×10^{-1}	
0.75	industrial_production	−0.000416794	0.002566842	8.711144×10^{-1}	
Note: *** p<0.001, ** p<0.01, * p<0.05					

Figure 18: QR Results at 90% Quantile

Quantile Regression Results (τ = 0.90)					
Quantile	Variable	Coefficient	Std. Error	P-value	Signif
0.90	(Intercept)	0.049975871	0.004033659	0.000000	***
0.90	volatility	0.014271603	0.004738006	2.805528×10^{-3}	**
0.90	term_spread	−0.007250670	0.003902483	6.411303×10^{-2}	
0.90	oil_prices	0.002940252	0.003246325	3.657824×10^{-1}	
0.90	inflation	0.000407026	0.003958187	9.181625×10^{-1}	
0.90	industrial_production	−0.001734626	0.003278624	5.971310×10^{-1}	
Note: *** p<0.001, ** p<0.01, * p<0.05					

Figure 19: QR Results at 95% Quantile

Quantile Regression Results (τ = 0.95)

Quantile	Variable	Coefficient	Std. Error	P-value	Signif
0.95	(Intercept)	0.062357379	0.004393968	0.000000	***
0.95	volatility	0.020412770	0.007055013	4.078704×10^{-3}	**
0.95	term_spread	−0.007624849	0.003595326	3.472748×10^{-2}	*
0.95	oil_prices	0.003963737	0.003358009	2.387442×10^{-1}	
0.95	inflation	−0.003081439	0.002972374	3.006793×10^{-1}	
0.95	industrial_production	−0.001169795	0.004175936	7.795647×10^{-1}	

Note: *** p<0.001, ** p<0.01, * p<0.05

Figure 20: QR Coefficient Significance Heatmap

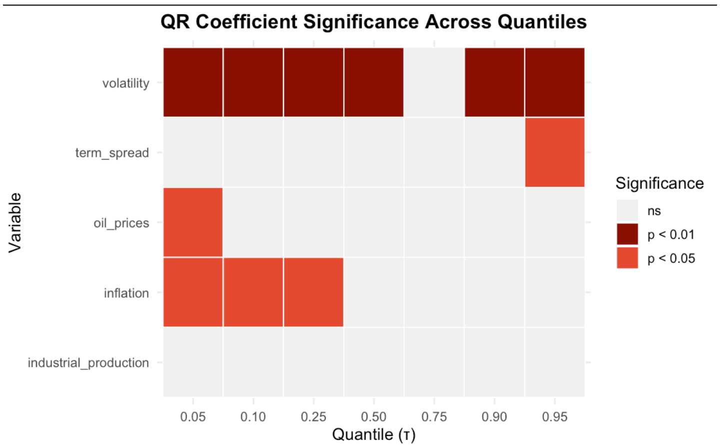


Figure 21: QR Coefficient Process Plot

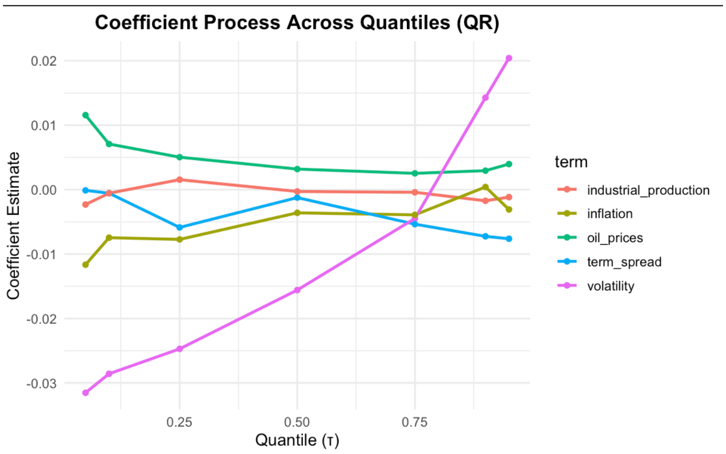


Figure 22: QR Cross Quantile Test Results

Cross-Quantile Tests (Coefficient Differences)

Variable	Diff	SE (Diff)	Z	P-value	Signif
τ=0.05 vs τ=0.95					
(Intercept)	−0.118085	0.006453	−18.298401	8.521407×10^{-75}	***
volatility	−0.051945	0.008539	−6.083133	1.178566×10^{-9}	***
term_spread	0.007508	0.006684	1.123250	2.613315×10^{-1}	
oil_prices	0.007597	0.006504	1.168069	2.427790×10^{-1}	
inflation	−0.008575	0.007033	−1.219277	2.227391×10^{-1}	
industrial_production	−0.001148	0.006122	−0.187525	8.512490×10^{-1}	
τ=0.1 vs τ=0.9					
(Intercept)	−0.095044	0.005303	−17.921241	8.051146×10^{-72}	***
volatility	−0.042855	0.005852	−7.323214	2.421006×10^{-13}	***
term_spread	0.006694	0.004852	1.379450	1.677561×10^{-1}	
oil_prices	0.004136	0.005838	0.708435	4.786753×10^{-1}	
inflation	−0.007867	0.005330	−1.476132	1.399083×10^{-1}	
industrial_production	0.001172	0.005175	0.226477	8.208308×10^{-1}	
τ=0.25 vs τ=0.75					
(Intercept)	−0.051727	0.005041	−10.261075	1.055256×10^{-24}	***
volatility	−0.020234	0.006234	−3.245567	1.172172×10^{-3}	**
term_spread	−0.000508	0.004513	−0.112501	9.104261×10^{-1}	
oil_prices	0.002510	0.005479	0.458195	6.468122×10^{-1}	
inflation	−0.003811	0.005488	−0.694274	4.875106×10^{-1}	
industrial_production	0.001960	0.004858	0.403512	6.865718×10^{-1}	
τ=0.05 vs τ=0.5					
(Intercept)	−0.060138	0.005598	−10.742381	6.436255×10^{-27}	***

Note: *** p<0.001, ** p<0.01, * p<0.05

Cross-Quantile Tests (Coefficient Differences)

Variable	Diff	SE (Diff)	Z	P-value	Signif
volatility	−0.015941	0.005375	−2.965738	3.019580×10^{-3}	**
term_spread	0.001124	0.006230	0.180372	8.568606×10^{-1}	
oil_prices	0.008374	0.006348	1.319224	1.870942×10^{-1}	
inflation	−0.008054	0.007099	−1.134517	2.565777×10^{-1}	
industrial_production	−0.002030	0.005629	−0.360618	7.183853×10^{-1}	
τ=0.95 vs τ=0.5					
(Intercept)	0.057947	0.005940	9.756028	1.738311×10^{-22}	***
volatility	0.036004	0.008889	4.050456	5.111794×10^{-5}	***
term_spread	−0.006385	0.005498	−1.161168	2.455737×10^{-1}	
oil_prices	0.000778	0.005963	0.130394	8.962548×10^{-1}	
inflation	0.000520	0.005046	0.103153	9.178413×10^{-1}	
industrial_production	−0.000882	0.004897	−0.180026	8.571322×10^{-1}	
τ=0.1 vs τ=0.5					
(Intercept)	−0.049479	0.004961	−9.973755	1.985768×10^{-23}	***
volatility	−0.012991	0.005362	−2.422823	1.540041×10^{-2}	*
term_spread	0.000683	0.005041	0.135567	8.921633×10^{-1}	
oil_prices	0.003890	0.006197	0.627679	5.302144×10^{-1}	
inflation	−0.003858	0.005178	−0.745142	4.561859×10^{-1}	
industrial_production	−0.000275	0.005000	−0.054909	9.562107×10^{-1}	
τ=0.9 vs τ=0.5					
(Intercept)	0.045565	0.005338	8.536760	1.380380×10^{-17}	***
volatility	0.029863	0.006362	4.693758	2.682307×10^{-6}	***
term_spread	−0.006010	0.004744	−1.266924	2.051823×10^{-1}	

Note: *** p<0.001, ** p<0.01, * p<0.05

Cross-Quantile Tests (Coefficient Differences)

Variable	Diff	SE (Diff)	Z	P-value	Signif
oil_prices	−0.000246	0.005407	−0.045494	9.637139×10^{-1}	
inflation	0.004009	0.005291	0.757672	4.486476×10^{-1}	
industrial_production	−0.001447	0.004468	−0.323748	7.461285×10^{-1}	

Note: *** p<0.001, ** p<0.01, * p<0.05

Figure 23: (TVQR) Coefficient Process Plot

Figure 24: BQR Results from 5% to 25% Quantile

Bayesian Quantile Regression: Posterior Summaries

Variable	Bayes Estimate	lower	upper	adj.lower	adj.upper
1					
(Intercept)	−0.296710	−0.560596	−0.111456	−0.849190	0.255770
volatility	−0.090400	−0.284321	0.058621	−0.418423	0.237624
term_spread	0.001456	−0.146573	0.143674	−0.203730	0.206641
oil_prices	0.019233	−0.118221	0.161503	−0.173369	0.211835
inflation	−0.052702	−0.232536	0.080417	−0.321982	0.216577
industrial_production	0.012058	−0.112738	0.149228	−0.161787	0.185904
2					
(Intercept)	−0.146541	−0.271872	−0.054135	−0.325702	0.032620
volatility	−0.051607	−0.160021	0.037444	−0.188460	0.085245
term_spread	−0.001934	−0.090285	0.083107	−0.103509	0.099641
oil_prices	0.012528	−0.073958	0.102103	−0.092020	0.117075
inflation	−0.029100	−0.132911	0.053460	−0.156753	0.098553
industrial_production	0.007491	−0.086213	0.108751	−0.124496	0.139478
3					
(Intercept)	−0.050483	−0.105535	−0.004681	−0.104424	0.003458
volatility	−0.027055	−0.085068	0.026723	−0.087993	0.033884
term_spread	−0.002140	−0.053798	0.049527	−0.053993	0.049712
oil_prices	0.007475	−0.045744	0.061938	−0.048882	0.063831
inflation	−0.012354	−0.071796	0.039281	−0.074769	0.050060
industrial_production	0.003146	−0.064786	0.075190	−0.094067	0.100359

Figure 25: BQR Results at the 50% Quantile

Bayesian Quantile Regression: Posterior Summaries

Variable	Bayes Estimate	lower	upper	adj.lower	adj.upper
4					
(Intercept)	0.000989	−0.036547	0.038671	−0.033584	0.035562
volatility	−0.013084	−0.058720	0.033686	−0.061414	0.035246
term_spread	−0.002655	−0.045536	0.040260	−0.043743	0.038432
oil_prices	0.004614	−0.040961	0.050558	−0.042200	0.051427
inflation	−0.004475	−0.051288	0.041720	−0.054607	0.045657
industrial_production	0.001046	−0.057304	0.061864	−0.080799	0.082892

Figure 26: BQR Results from 75% to 95% Quantile

Bayesian Quantile Regression: Posterior Summaries

Variable	Bayes Estimate	lower	upper	adj.lower	adj.upper
5					
(Intercept)	0.053028	0.007140	0.107635	−0.001472	0.107529
volatility	0.002587	−0.052072	0.062662	−0.062001	0.067175
term_spread	−0.003851	−0.056085	0.048978	−0.057243	0.049541
oil_prices	0.002215	−0.052392	0.055705	−0.053838	0.058268
inflation	0.002583	−0.049137	0.060927	−0.058259	0.063426
industrial_production	−0.001344	−0.069828	0.064677	−0.090987	0.088299
6					
(Intercept)	0.152482	0.055929	0.283584	−0.040582	0.345545
volatility	0.027743	−0.064911	0.139848	−0.121382	0.176868
term_spread	−0.006991	−0.095843	0.082746	−0.114504	0.100522
oil_prices	−0.002060	−0.091525	0.083202	−0.104473	0.100354
inflation	0.019005	−0.061880	0.121566	−0.104586	0.142596
industrial_production	−0.005591	−0.105297	0.086122	−0.132684	0.121502
7					
(Intercept)	0.305041	0.116298	0.568839	−0.264734	0.874815
volatility	0.067614	−0.088796	0.267978	−0.274984	0.410212
term_spread	−0.011958	−0.154026	0.134305	−0.216013	0.192098
oil_prices	−0.007961	−0.152936	0.130217	−0.202547	0.186625
inflation	0.044704	−0.085740	0.221978	−0.216982	0.306390
industrial_production	−0.012621	−0.150260	0.108354	−0.182477	0.157236

Figure 27: BQR Cross Quantile Test Results

Bayesian Quantile Regression: Cross-Quantile Tests

Variable	Diff	SE (Diff)	Z	P-value
(0.05, 0.50)				
(Intercept)	0.297699	0.116172	2.562567	1.039016×10^{-2}
industrial_production	−0.011012	0.073418	−0.149996	8.807681×10^{-1}
inflation	0.048228	0.083286	0.579059	5.625490×10^{-1}
oil_prices	−0.014619	0.075080	−0.194714	8.456171×10^{-1}
term_spread	−0.004111	0.077210	−0.053245	9.575366×10^{-1}
volatility	0.077316	0.090605	0.853325	3.934793×10^{-1}
(0.05, 0.95)				
(Intercept)	0.601751	0.162650	3.699662	2.158868×10^{-4}
industrial_production	−0.024679	0.093906	−0.262805	7.927009×10^{-1}
inflation	0.097406	0.111963	0.869986	3.843083×10^{-1}
oil_prices	−0.027194	0.101536	−0.267825	7.888339×10^{-1}
term_spread	−0.013414	0.104367	−0.128522	8.977356×10^{-1}
volatility	0.158014	0.126242	1.251670	2.106901×10^{-1}
(0.10, 0.50)				
(Intercept)	0.147530	0.058766	2.510452	1.205767×10^{-2}
industrial_production	−0.006445	0.058291	−0.110561	9.119645×10^{-1}
inflation	0.024625	0.053135	0.463448	6.430434×10^{-1}
oil_prices	−0.007914	0.050619	−0.156342	8.757637×10^{-1}
term_spread	−0.000721	0.049351	−0.014618	9.883370×10^{-1}
volatility	0.038523	0.055616	0.692660	4.885227×10^{-1}
(0.10, 0.90)				
(Intercept)	0.299023	0.080362	3.720961	1.984659×10^{-4}
industrial_production	−0.013082	0.069700	−0.187688	8.511210×10^{-1}

Bayesian Quantile Regression: Cross-Quantile Tests

Variable	Diff	SE (Diff)	Z	P-value
inflation	0.048106	0.066711	0.721100	4.708480×10^{-1}
oil_prices	−0.014587	0.063277	−0.230531	8.176795×10^{-1}
term_spread	−0.005057	0.063499	−0.079642	9.365217×10^{-1}
volatility	0.079350	0.072567	1.093479	2.741838×10^{-1}
(0.25, 0.75)				
(Intercept)	0.103511	0.036320	2.849967	4.372383×10^{-3}
industrial_production	−0.004490	0.049522	−0.090660	9.277630×10^{-1}
inflation	0.014938	0.039891	0.374466	7.080575×10^{-1}
oil_prices	−0.005260	0.038923	−0.135130	8.925091×10^{-1}
term_spread	−0.001711	0.037591	−0.045507	9.637029×10^{-1}
volatility	0.029642	0.040865	0.725350	4.682374×10^{-1}
(0.90, 0.50)				
(Intercept)	−0.151493	0.061163	−2.476868	1.325408×10^{-2}
industrial_production	0.006637	0.057521	0.115389	9.081367×10^{-1}
inflation	−0.023480	0.052469	−0.447508	6.545083×10^{-1}
oil_prices	0.006673	0.050317	0.132627	8.944884×10^{-1}
term_spread	0.004336	0.050543	0.085784	9.316382×10^{-1}
volatility	−0.040827	0.057307	−0.712423	4.762028×10^{-1}
(0.95, 0.50)				
(Intercept)	−0.304052	0.117028	−2.598116	9.373676×10^{-3}
industrial_production	0.013667	0.072640	0.188144	8.507640×10^{-1}
inflation	−0.049179	0.082007	−0.599692	5.487112×10^{-1}
oil_prices	0.012575	0.075912	0.165649	8.684333×10^{-1}
term_spread	0.009302	0.076741	0.121219	9.035178×10^{-1}
volatility	−0.080698	0.094017	−0.858336	3.907070×10^{-1}

Figure 28: QR Performance Metrics

In-sample Quantile Regression Metrics

Quantile	Pinball loss	Pseudo R1 (KM)	Coverage
0.05	0.003691	0.345271	0.050157
0.10	0.006311	0.284235	0.106583
0.25	0.011742	0.178982	0.247649
0.50	0.015108	0.078732	0.495298
0.75	0.011986	0.012846	0.749216
0.90	0.006471	0.058362	0.905956
0.95	0.003773	0.079160	0.940439

Figure 29: BQR Performance Metric (mean-pinball)

Bayesian QR: Mean Pinball Loss by Quantile

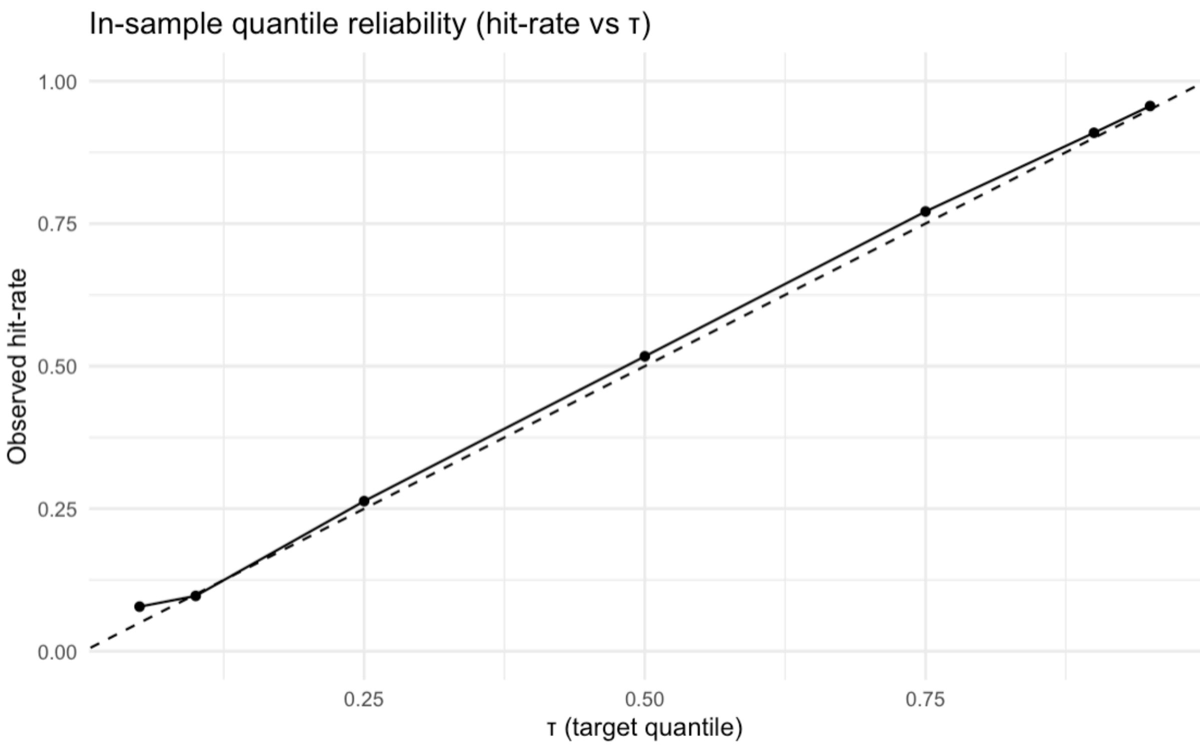
Quantile	Mean pinball loss
0.05	0.014938
0.10	0.014859
0.25	0.014375
0.50	0.015207
0.75	0.014414
0.90	0.015044
0.95	0.015149

Figure 30: TVQR Performance Metrics

TVQR: Mean Pinball Loss by Quantile

Quantile	Mean pinball loss
0.05	0.003050
0.10	0.005578
0.25	0.010604
0.50	0.013817
0.75	0.011101
0.90	0.006072
0.95	0.003372

Figure 31: Time Varying Quantile Reliability Plot



8.2 R Code

http://localhost:7572

Abstract: This master thesis examines whether macro-financial indicators contain predictive information for monthly STOXX Europe 600 log-returns, and whether these relationships are asymmetric across market states and unstable over time. Using a monthly dataset spanning January 1999 to August 2025, the study focuses on five widely used predictors implied like volatility (VSTOXX), term-spread shocks, oil-price changes, inflation, and industrial-production growth, to assess return predictability at both the center and the tails of the distribution.

Empirically, the analysis proceeds from a mean benchmark to distribution- and time-sensitive frameworks. A heteroskedasticity-robust OLS benchmark suggests predictability is weak on average, with volatility standing out as the most robust mean predictor. In contrast, Quantile Regression (QR) reveals pronounced heterogeneity. Volatility exhibits strong tail asymmetry, inflation matters primarily in the lower tail, and term-spread shocks become relevant in selected quantiles, while oil prices and industrial production display limited stable effects. Time-Varying Quantile Regression (TVQR) further shows that these quantile effects evolve across crises and calmer regimes, indicating that predictability, when present, is regime-dependent rather than constant. A Bayesian Quantile Regression (BQR) robustness check yields wide credible intervals spanning zero across predictors and quantiles, highlighting substantial parameter uncertainty at the monthly frequency.

In-sample evaluation confirms that TVQR delivers the lowest pinball loss and near-ideal quantile calibration, outperforming static alternatives. Overall, this study, among the few to focus specifically on the STOXX Europe 600, concludes that macro-financial predictability is it is best characterized as tail-dependent and time-varying and should be interpreted cautiously when uncertainty is fully accounted for.

Key words:

STOXX Europe 600, return predictability, macro-financial predictors, quantile regression, time-varying quantile regression, Bayesian quantile regression, tail risk, in-sample.

UNIVERSITÉ CATHOLIQUE DE LOUVAIN
Louvain School of Management
Place des Doyens, 1 bte L2.01.01, 1348 Louvain-la-Neuve
Boulevard Emile Devreux 6, 6000 Charleroi, Belgique
Chaussée de Binche 151, 7000 Mons, Belgique
www.uclouvain.be/lsm