OSCILLATING BETWEEN FEAR AND RELIEF:

A VOLATILITY BASED AGGREGATE MARKET RETURN-STATE MODEL

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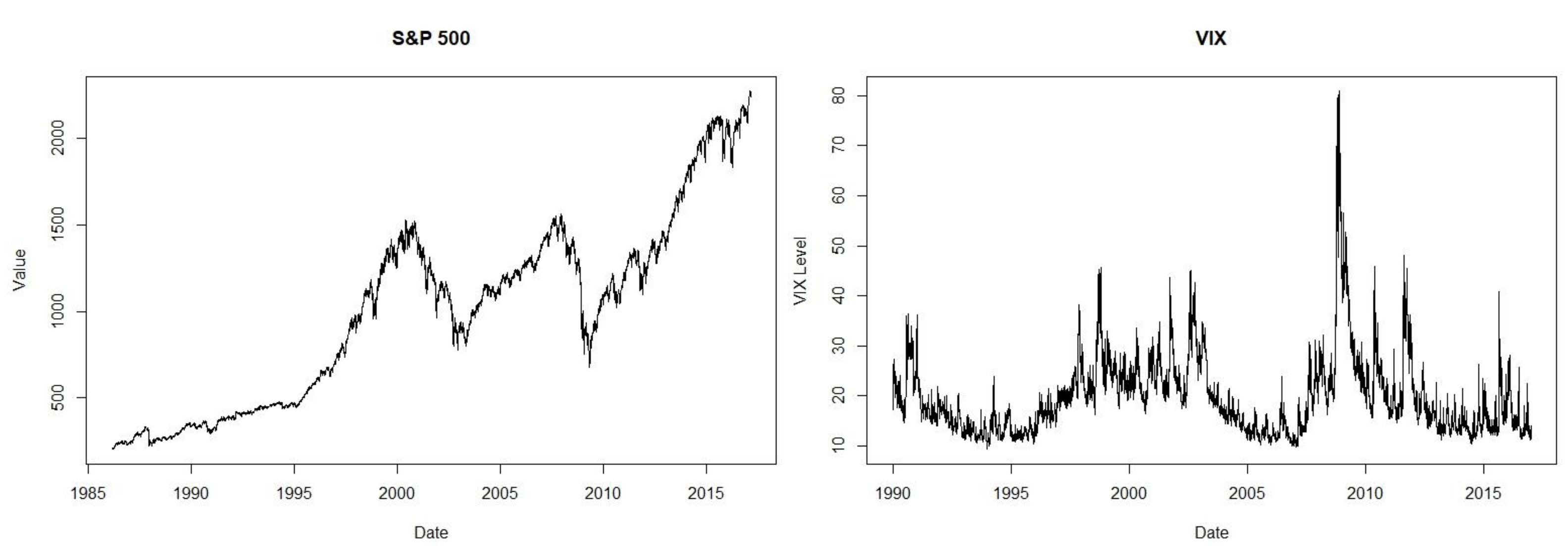
Abstract

- Explored implied volatility – market return relationships
- Distinguished between two state variables, implied volatility level and implied volatility changes.
- Found evidence for significant asymmetric and non-linear relationships between implied volatility variables and macro market returns.
- Volatility-based macro market return-states are found to rigorously filter for sign and magnitude of returns and have significantly different return expectations.
- Applications to managing tail risk and making investment decisions.

Research Question

Is there a generalizable relationship between aggregate market returns and implied volatility variables that can extend the predictions made by existing volatility forecasting models?

Background



- Volatility indices are widely used in hedging risk and are often referred to as "fear gauges" given their tendency to reflect the valence of this emotion in the broader market.
- Past research has demonstrated the prevalence of generalizable behavioural phenomena at the individual stock level.
- Investor psychology and emotion has long been the subject of behavioural finance research.
- Insofar as implied volatility reflects fear, market mood, investor emotion, and overall uncertainty, previous behavioural insights may lend themselves to the explanation of volatility-return anomalies.
- It has been shown empirically that a negative relation exists between returns and volatility and that negative returns have stronger impacts.
- There are several methods in use to forecast volatility and they can be roughly grouped into two general classes: Autoregressive Conditional Heteroscedasticity (ARCH) and Generalized ARCH (GARCH).
- It has been found that many such models perform well across methods, assets and subsamples.
- Empirical research has demonstrated that given longer time series implied volatility outperforms past volatility in forecasting future volatility and even subsumes the information content of past volatility in some specifications.

Methodology

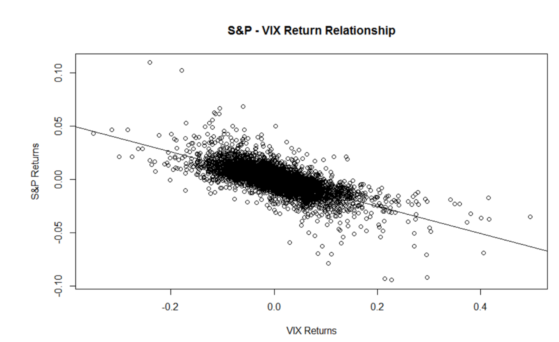
Collected daily data for the VIX and the S&P 500 spanning the time-period from January 1990 to July 2016. Examined relationships between the data sets with:

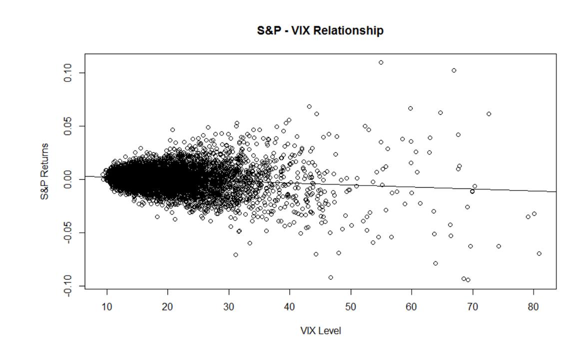
- Linear, nonlinear and quantile regressions
- Cross-sectional analyses including difference of mean tests
- Cross-sectional event studies to investigate market behaviour around observations
- Tests for Granger-Causality

Results

Regression Analysis:

- An ordinary least squares linear regression confirms that the previously established inverse relationship holds, with a statistically significant regression coefficient on VIX returns. Interpreted in its current form, as VIX returns increase, S&P returns decrease.
- Another such regression with VIX index level as the independent variable finds that the coefficient on the VIX index level is significant and negative. Thus, as the VIX index level increases, S&P returns decrease.
- A third multivariable regression finds that the coefficients on both VIX level and returns remain negative and statistically significant.

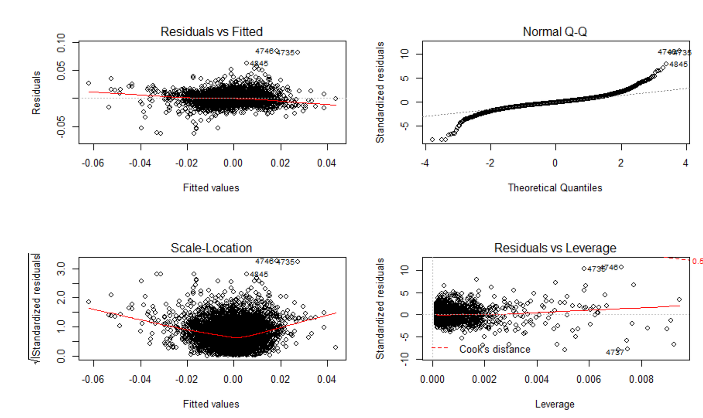


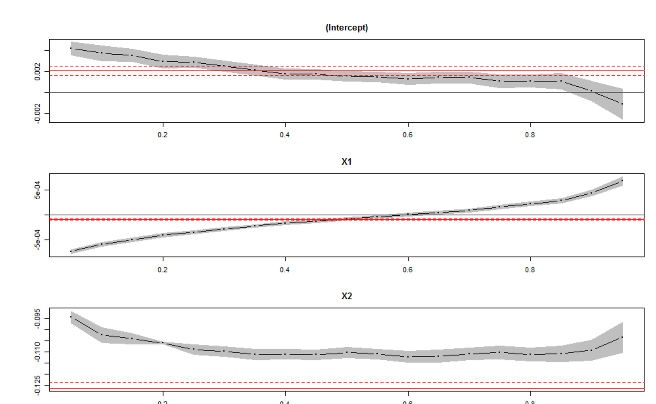


Nonnormality of Multivariable Regression Residuals:

- The fist plot indicates that there may be some nonlinear relationship
- The QQ plot shows the existence of heavy tails
- The Scale-Location plot highlights the presence of heteroskedasticity.
- The Residuals vs. Leverage plot indicates that there are no influential outliers.

Given this nonnormality, an area of particular interest is whether or not these relationships change across the quantiles of the S&P return distribution.





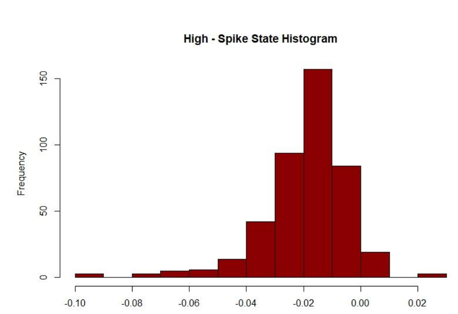
Linear Quantile Regression:

The plots on the right hand side above show the values of the coefficients and the intercept from the 5th to 95th percentiles, where X1 is the volatility level and X2 is the return on the volatility index.

- The relationship between market returns and both volatility level and volatility return changes across quantiles with continued statistical significance.
- Volatility return continues to have a negative coefficient, but it becomes less negative at the tail quantiles.
- The volatility level coefficient changes sign from the 5th to 95th percentiles. At lower quantiles, volatility level has a significantly negative relationship with market returns, but at higher quantiles it has a significantly positive relationship.

SAME DAY MEAN RETURNS				
	SPIKE	SOFT SPIKE	SOFT DROP	DROP
HIGH	-1.91%	-0.48%	0.32%	1.73%
LOW	-0.68%	-0.98%	0.25%	0.75%

PERCENTILE OF 0% RETURN				
	SPIKE	SOFT SPIKE	SOFT DROP	DROP
HIGH	95	76	33	6
LOW	86	60	30	9



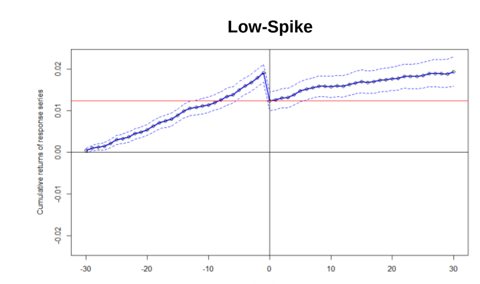
Cross Sectional Analysis:

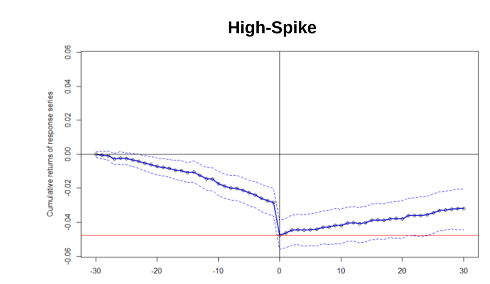
- Volatility levels and returns are divided into quantiles to investigate market returns in the cross section.
- For same day returns, the null hypothesis is rejected for all state comparisons, and therefore, states appear to differ significantly.
- A significant majority of returns for each "state" are of the same sign as the mean.

Event Studies:

Each study plots the mean cumulative returns, as well as, the 97.5 and 2.5 percentile confidence bands for observations spanning the 61 trading-day window around each event time (state instance).

- The largest and most significant one day move appears to occur at time 0.
- The 30-day window leading up to event time always exhibits significantly negative returns when volatility index levels are high.
- When volatility index levels are low, cumulative returns leading up to event time are always positive.
- Cumulative returns following event times are never significantly negative for any state and are significantly positive over longer time intervals for all cross sections except the "High-Drop" state.



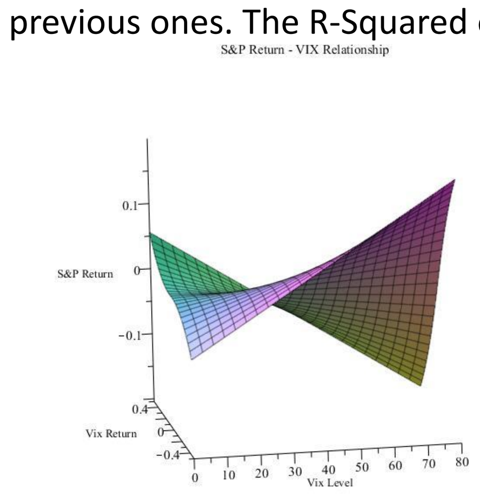


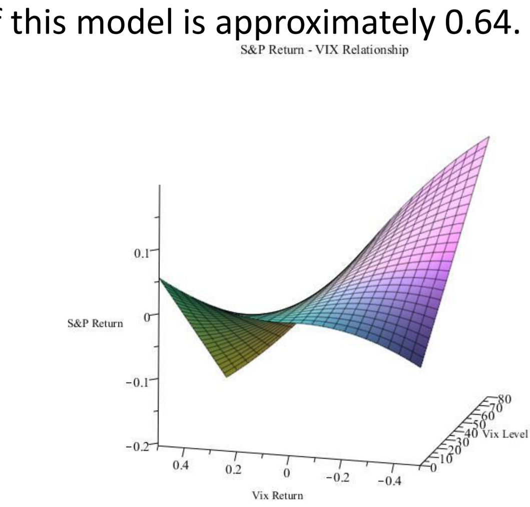
Nonlinear Regression:

This regression attempts to test what previously appeared to be a nonlinearity in the response of S&P returns to VIX index levels and VIX returns by incorporating additional variables that represent nonlinear transformations of the initial independent variables.

$$r_m = \alpha + \beta V_L + \gamma V_L V_R + \delta V_R + \vartheta V_R |V_R| + \varepsilon ,$$

where V_L is the VIX level, V_R is the VIX return, r_m is the return of the market, and the intercept, α, and coefficients are the values supplied by the regression output. The results indicate that all independent variables are significant and that the new model explains a greater proportion of the variation of S&P returns than the previous ones. The R-Squared of this model is approximately 0.64.





Implications

- High volatility states have a negative expected daily return and low volatility states have a positive expected daily return.
- Given that these state characterizations are persistent a priori, this calls into question market efficiency.
- The success of volatility forecasting models presents a distinct opportunity to dynamically adjust market positions to capitalize on the predictability of return sign.
- The probability of a positive or negative return observation conditioned on the probability of a cross section occurring allows for probabilistic forecasts of next day market returns.
- This creates an opportunity for investors and risk managers to exploit higher return potential without assuming the corresponding risk.

Conclusion

- There exists significant and compelling evidence for different market states and a dynamic volatility-return relationship across quantiles.
- Tests of the relationship seem to indicate that in addition to the inverse relationship between market returns and both volatility levels and returns, volatility returns and market returns vary nonlinearly and absolute volatility levels influence the magnitude of the volatility return – market return response.
- The cross-sectional analysis of volatility returns and level on market returns also proves itself to be a rigorous filter of the sign and magnitude of returns, particularly at the extremes.
- Avenues for future research include extensions to other markets and asset classes, an examination of intraday impacts, and a deeper exploration of applicable volatility-return relationship models.