More research on using correlation and volatility in trading signals

References

Evaluating correlation breakdowns during periods of market volatility – Mico Loretan

Using correlation in trading – Sofien Kaabar

The relative volatility index, deriving trading signals from fluctuations – Sofien Kaabar

The flashing indicator, combining correlation and volatility to generate trading signals

Abnormal sector option correlation premiums and predictable changes in implied volatility

Financial indicators signalling correlation changes in sovereign bond markets

Notes

One difficulty: correlation can differ in periods of heightened market volatility (compared to quiet markets) – during major market events, correlations change dramatically (bookstaber 1997)

Tempting to explain increased correlation of returns during hectic market periods as the result of a shift in the joint distrib of asset returns, owing to contagion of some markets by others / the particular nature of the shocks / changes in market structure and practices

But unless one has a model of when such periods are likely to arise (or at least how often) and what particular pattern of correlations will ensue -> this approach makes it very hard to properly hedge

Because the relationship is essentially unknown

*Could we use the correlation between our two assets and a third one as a trading signal ?*

*It would probably inform us on the stochasticity of the correlation between our own two assets*

*Could we use the maximum drawdown ?* – largest historical loss of an asset

Introduction to trading signals and how they are used (very briefly, it will be an opening)

explain the use in our context – additional info that is fed to the algorithm to consider for potential future moves in the volatility or the correlation of two (or more) assets

volatility: measures how a single asset prices fluctuate -> stochastic but assumed constant

correlation: measures how the combined asset prices of two assets can fluctuate -> stochastic but assumed constant

my own reasoning: can we implement a third underlying asset with high static correlation with the two we already consider -> compute the implied volatility of an ATM put option on that third asset, as well as the stochastic correlation between that third asset and our two considered

the idea being that we might observe patterns between how the volat/correl change, and how the prices of our two assets change as well -> might allow us to better predict sudden moves in those two assets, which could therefore increase the accuracy and efficiency of our hedging strategy

testing for autocorrelation to predict price moves -> seems like a very good idea

why would we need to consider autocorrelation in our delta hedging strategy

autocorrelation tells us how the stock’s returns relate to its returns in previous trading sessions

if the stock exhibits autocorrelation: past returns therefore do seem to influence future returns

so that past returns are a very good predictor of future returns for this particular stock

there is also serial correlation (similar concept)

it measures the relationship between a variable’s current value given its past values

when a variable and a lagged version of itself are correlated over periods of time

indicator used to determ how well the past price of a security predicts the future price

stocks with high degree of serial correlation / autocorrelation will exhibit patterns, and allow for traders to recognize and predict futures stock moves

serial correlation among these quants is determined using the Durbin-Watson test

the correlation can be either positive or negative (positive or negative patterns)

security that has a negative serial correlation has a negative influence on itself over time

ok donc il y a cette idée qu’on souhaite se hedge en forecastant des mouvements futurs de stocks

et on sait pas vraiment s’ils seront très différents des périodes précédentes ou pas

si jamais ils ont tendance à être vachement différent, notre stratégie aura une incentive à naturellement trop (ou pas assez) hedge en vu de ces potentiels mouvements, pour être en ligne avec le marché

l’autocorrélation des returns d’un actifs pourrait très bien être cet indicateur, et pourrait inciter l’algorithme à produire une stratégie soit très en ligne avec l’historique des returns (autocorrel assez forte), soit possiblement innovante (pas d’autocorrel : tendance à bouger sans signaux préalables)

<https://www.sciencedirect.com/science/article/abs/pii/S1057521920302428>

stock returns, quantile autocorrelation and volatility forecasting – Yixiu Zhao

they examine stock return autocorrelation at various quantiles of the returns distribution and use it to forecast stock return volatility

keywords: quantile autoregression / stock returns / volatility forecasting / volatility asymmetry

evening 16/03 research

**the paper examines stock return autocorrel at various quantiles of returns distrib**

strength of autoregression varies across quantiles of the returns distrib

**they use quantile estimators of returns to forecast stock return volatility**

they show that the quantile autoregressive (QAR) framework improves out-of-sample volatility forecasting perf, compared to generalized autoregressive conditional heteroskedasticity (GARCH) type models and other quantile-based models

*research on that paper: 17/03*

quantile autoregression and volatility forecasting

research on volatility forecasting is abundant

use of models from the autoregressive conditional heteroskedasticity (ARCH)

and generalised autoregressive conditional heteroskedasticity (GARCH)

this paper proposes a new method to generate volatility forecasts

the volatility forecasts produced by other models are based on the assumption that the shape of the conditional distribution is fixed over time

but returns and volat distrib of assets is more often heterogeneous

quantile regression is immune to this parametric model problem

and this type of analysis can provide greater insight into the interdependence of variables across the whole distribution

this study proposes a quantile autoregressive method that accommodates autocorrelation in stock returns at various quantile levels in order to generate volatility forecasts

those forecasts are likely to be more accurate due to its ability to deal with temporal variation in the returns distribution

quantile partial autoregressive function (QPACF)

such analysis shows that at the median of the returns distrib – the impact from past returns is relatively weak as no significant/persistent dependence pattern in stock return is detected

in contrast the analysis produced for lower/upper quantiles reveal persistent dependence patterns for stock returns

they show that the lower quantiles of the current returns distrib are pos dependent on past returns

their forecasting method significantly outperforms most of the MS-GARCH type models

and also all other quantile-based models

these results are robust in out-of-sample forecast comparisons

Trapin (2017) shows that autoregressive dependence is strong and persistent in both tails of the returns distribution

lower quantiles (contain negative returns) denote bad times for the market

upper quantiles (contain positive returns) signal good times for the market

they find that future stock returns are negatively correlated with past returns when the market is experiencing good times (while they exhibit positive autocorrel in bad times)

the main purpose of this paper is to investigate stock returns quantile autocorrelation and use the resulting autocorrelation pattern to generate volatility forecasts for financial assets

they apply the sample QPACF to determ the dependence pattern between past returns and quantiles of the current return distrib

to then evaluate the predictive ability of past returns for =/= sections of the returns distrib (based on the varying order of significant lags)

volatility forecasting model

three steps

**step one**: specify the QAR model for stock returns using an appropriate lag structure

optimum lag order is determ via the method described previously

**step two**: we obtain conditional density forecasts for stock returns

**step three**: obtain the volatility forecasts for a given stock return