# An Enhancement to Xantos' Systematic Model

August 2022

## Executive Summary

This study illustrates the performance gains from incorporating dynamic conditional volatility and covariance forecasts into our systematic investment process. Results indicate that explicitly modeling the dynamics of the conditional covariance matrix increases risk-adjusted returns for more aggressive portfolios and outperforms the market by more than the baseline Xantos algorithm does.

**Key takeaways**

- For moderate to aggressive risk profiles, the updated model significantly outperforms our baseline.
- For a conservative risk tilt, our baseline model performs better on a risk-adjusted basis.
- The peak difference in annualized performance is large, as much as 2 percent on an annualized basis. Further work will explore best of both models, combining time-varying conditional volatility approach with lower partial moments.

## Introduction

It is well established that the volatility and covariance of financial times series such as equity returns, and exchange rates exhibit temporal dependence i.e., time matters, market returns yesterday might impact today's return. In practice, this means that daily return volatility and covariance tend to cluster together – a day of high stock return volatility is more likely than not to be followed by another day with high stock return volatility. Similarly, strong co-movement between the market returns of two assets on any given day is more likely to be followed by strong co-movement between those assets on the next trading day.

The importance of this is that financial market participants can improve forecast performance by accounting for the dynamic nature of return volatility, ultimately improving risk management. The class of models we consider is based on the dynamic conditional correlation (DCC) specification of Engle (2002) which itself is within the class of multivariate generalized autoregressive conditional heteroskedasticity (MGARCH) models. MGARCH models commence from the viewpoint that volatility varies over time (heteroskedastic) and that this variability might be affected by the volatility of other assets (multivariate). In addition, the DCC approach specifies the conditional correlation matrix through a dynamic equation. Thus, the DCC specification explicitly accounts for dynamic temporal co-dependence and provides useful albeit computationally expensive techniques for forecasting conditional variance and volatility.

A key caveat is that these approaches model the dynamic covariance matrix as deterministic functions of the volatility of past daily returns – in contrast to stochastic volatility methods. Nevertheless, these approaches are useful for assessing conditional risk/return tradeoffs in a portfolio.

## Environment and Calibration

Our baseline model today makes use of rolling windows to estimate lower partial moments between assets in the portfolio. While this partially mitigates concerns about mis-specifying the dynamic nature of the joint dependence structure across assets within the portfolio, it is limited in its forecasting potential.

Rendering explicit the dynamic relationship between current covariance matrix and historical covariances reduces biases in conditional mean and volatility estimates and offers better predictive performance. To explore this, we focused on the multi-decade period between December 2002 and May 2022 using a predefined investable uniervse[1].

The rebalance is set to monthly and a minimum offset for trades is set to 5 percent which helps eliminate frivolous portfolio rebalancing and reduces incurred taxes. The nominal portfolio amount is set to $100,000 at trade inception with

[1] Investable universe includes PGR, FTNT, TEAM, MKC, CPRT, FRHC, ZTS, TMO, MSCI, AMZN, VEEV, SHOP, MTD, WAT, NFLX, MSFT, MA, BKNG, INTU, ASML, CRM, MEDP, CSGP, SQ, WD, MKTX, AEP, WEC, PEG, INMD, TLT, SHY, IEF, IGOV.

no recurring deposits or dollar cost averaging. For simplicity fractional trading is enabled. Any and all dividends are reinvested into the portfolio and tax loss harvesting is disabled. A 100bps annual advisory fees is included and the benchmark index is defined as the S&P 500 Index.

A key parameter, **spread**, is used in our models to specify the aggressiveness of the portfolio. At higher spreads, the allocator shifts capital towards higher growth/higher volatility assets and vice versa. While the backtest environment supports Xantos' macro forecasting environment which adjusts the aggressiveness of the portfolio in response to macroeconomic developments, also known as business cycle predictor (or BCP), we disabled this feature to evaluate the efficacy of the underlying models all else equal.

The backtest environment mimics trading controls and other key features deployed in customer accounts such as exposure limits and dividend re-investments for example. Data is simulated forward thus eliminating look-ahead bias i.e., only information present on any given day is used in allocating funds across assets and in executing trades. Differently from real accounts, the environment does not account for the timing of cash flows. Furthermore, closing prices are used so that orders execute at the next close with a T+2 expiration window. The rebalancing interval is set to monthly.

Additionally, short-sales are disabled leading to a long-only portfolio throughout the trading period. Maximum individual security exposures are limited to 30 percent for all securities, with tighter regional exposure limits for foreign company stocks via listed American depositary receipts (ADRs) and bond ETFs.

## Results

Our backtest results demonstrate that the revised model delivers higher returns for aggressive investors as it increases the annualized returns while confining the volatility in a reasonable range. The degree of aggressiveness is defined as the target outperformance relative to the benchmark index. The figures below illustrate key performance and risk metrics for different spread values – i.e., the target annualized return relative to the S&P 500 expected return – for the baseline Xantos default vs the Revised Model approach.

**Figures 1 & 2** below illustrate that the Revised Model yields higher annualized net returns for higher target spreads. The gains in performance for the benchmark portfolio are realized for spreads above 20 percent. The outperformance of the Revised Model in terms of annualized net returns peaks at a 30.0 percent spread and starts to decline afterward. This is likely because further gains require greater concentration and thus larger drawdowns in bad periods (more below). The peak performance gain is large, slightly over 200 basis points on an annualized basis. For lower spreads, or a more conservative portfolio, the baseline approach – which pays particular attention to downside risk and negative co-movement between assets – outperforms on an annualized basis.

To properly assess the performance of the two approaches, one has to consider risk-adjusted metrics such as the Sharpe ratio (defined later), which accounts for the volatility of the portfolio returns on an annualized basis. As we may expect, in **Figure 3** aggressive investing strategies yield more volatile portfolios since they take more risks. Conversely, more conservative targets i.e., lower spreads yield less volatility. This suggests that the Revised Model is closer to the efficient frontier for aggressive spreads as it yields higher performance for similar volatility.

The Sharpe ratio is defined as the ratio of the portfolio's excess return over the risk-free rate to the standard deviation of the portfolio's excess return. In other words, returns per unit risk. It is one way of summarizing the combination of returns and volatility illustrated above and is incredibly useful for assessing a portfolio's performance normalized for risk. Specifically, a higher Sharpe ratio means the portfolio has better risk-adjusted-performance.

Congruent with the annualized return and volatility results displayed above, the Revised Model yields higher Sharpe ratios for more aggressive parameterizations of the Xantos environment while the Default model yields higher Sharpe ratios for more conservative parameterizations. An interesting result which bears more investigation is that the Revised Model displays a steady Sharpe ratio profile as the target spread increases while the Default Model shows a slight downward sloping profile.

Another important metric is the Max Drawdown (MDD) which is the worst return from a recent peak. It measures how much an investor could have lost after a peak during a market downturn. While volatility is a useful statistical measure, the MDD is probably closer to the measure of risk that concerns the average investor. Much of the original modeling in the Default Model approach was designed with the MDD in mind. **Figure 4** shows a comparison of the Default and Revised approaches for various degrees of portfolio aggression.

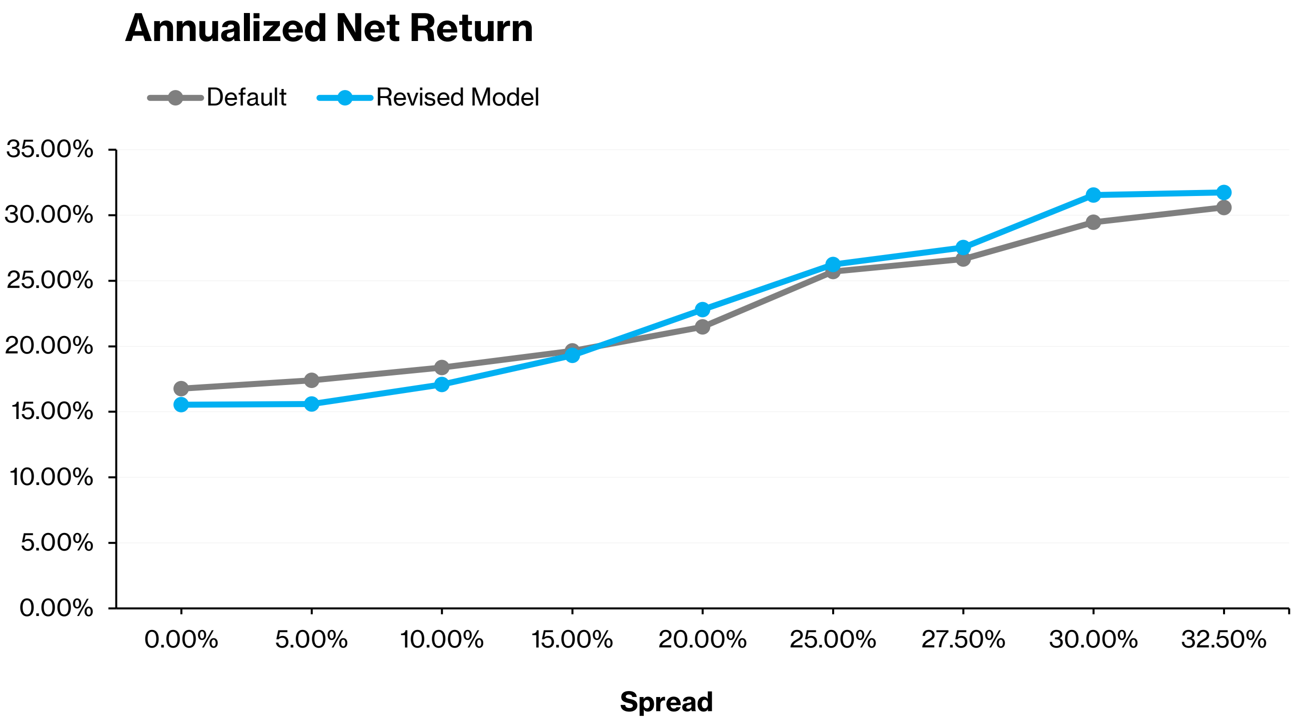
For this measure of risk, the Revised Model underperforms the Default in that it leads to larger max drawdowns across all but one level of aggression. As can be expected, the MDD increases (gets more negative) as the portfolio aggression increases.

## Conclusions

Introducing dynamic conditional volatility forecasts delivers higher risk-adjusted performance gains for aggressive portfolios in the Xantos backtesting environment. For a conservative risk tilt as reflected by lower spreads, the baseline (Default) Xantos performs better on a risk-adjusted basis. The results suggest that modeling the dynamic nature of the dependence structure across assets within the portfolio is worth the extra computational costs.

Future research will attempt to harmonize the key concepts in both models by combining the dynamic modeling methods with an emphasis on lower partial moments.

We would like to thank **Luyang Zhang** from the University of California Santa Barbara for his immense contribution to this work during his Summer Internship at Xantos.



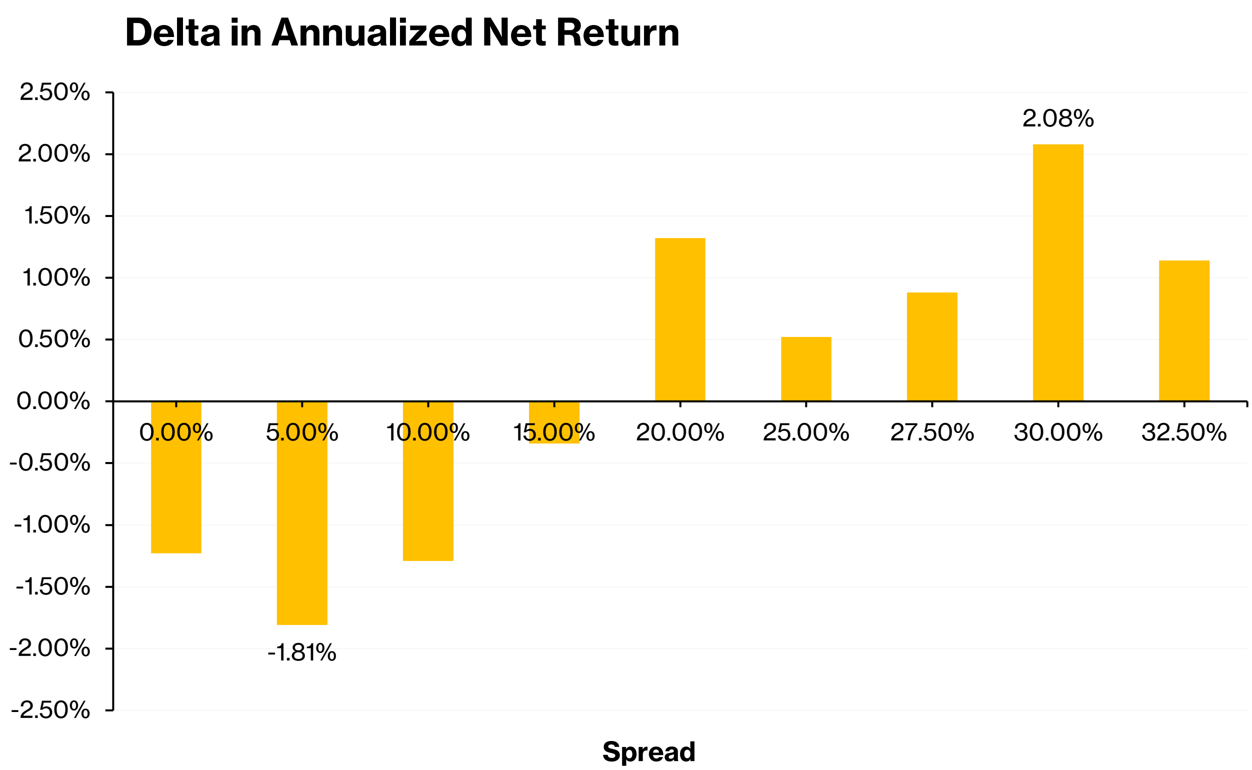




**Figure 1:** Annualized net returns and difference in returns for Baseline (Default) model versus Revised model across different spreads (or aggressive profile). Stats based on monthly returns from inception of 12/2002 till 05/2022. Benchmark is S&P 500 Index. Past performance is not a guarantee of future performance.

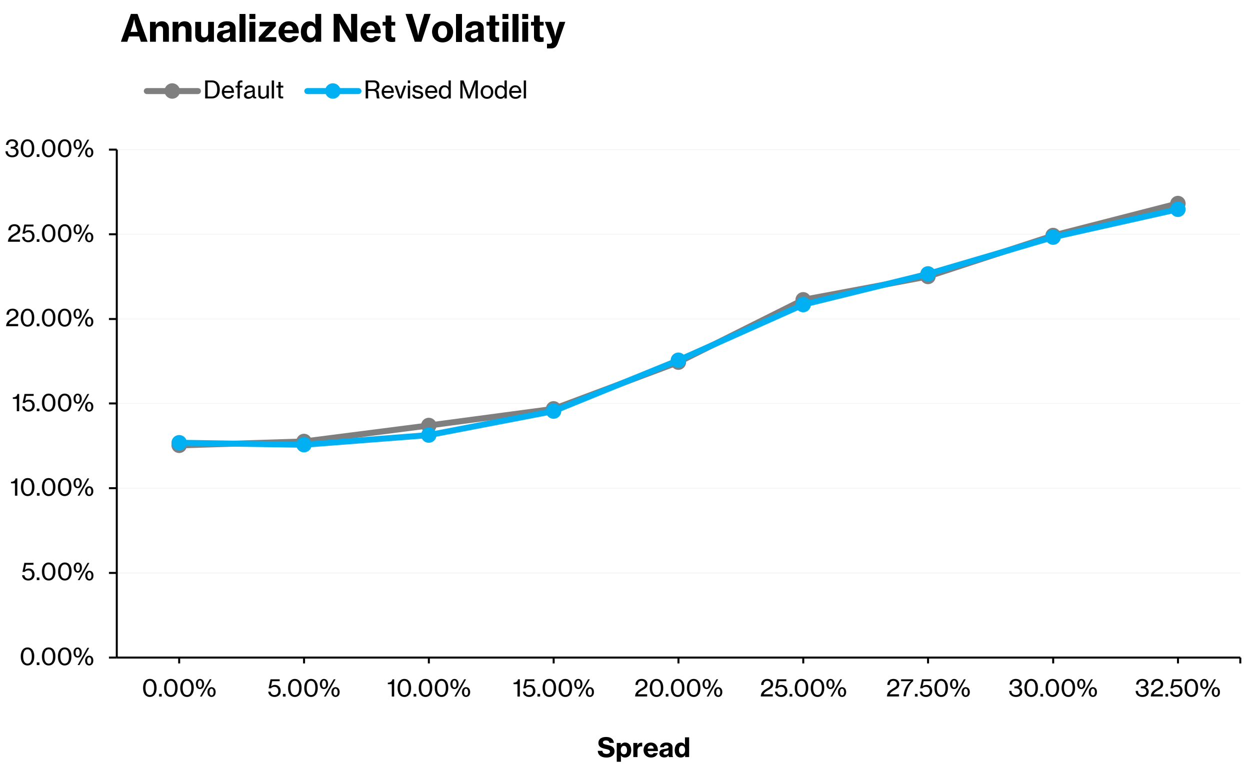



**Figure 2:** Annualized net volatility in returns for Baseline (Default) model versus Revised model across different spreads (or aggressive profile).

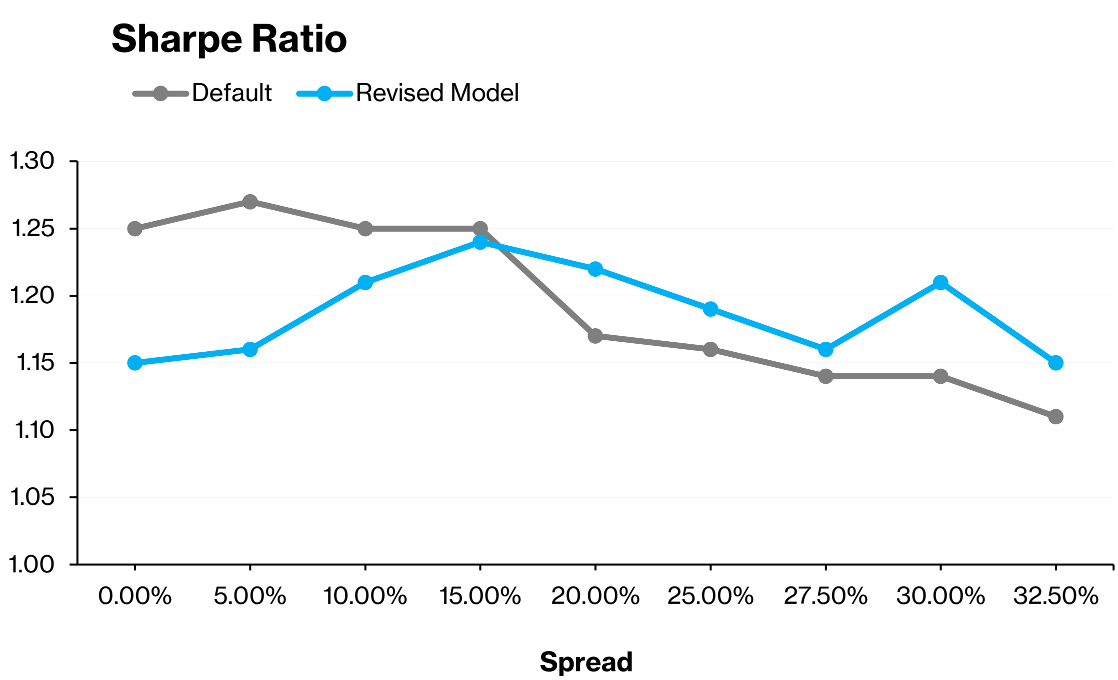



**Figure 3:** Annualized risk-adjusted return –or Sharpe ratio for Baseline (Default) model versus Revised model across different spreads (or aggressive profile).

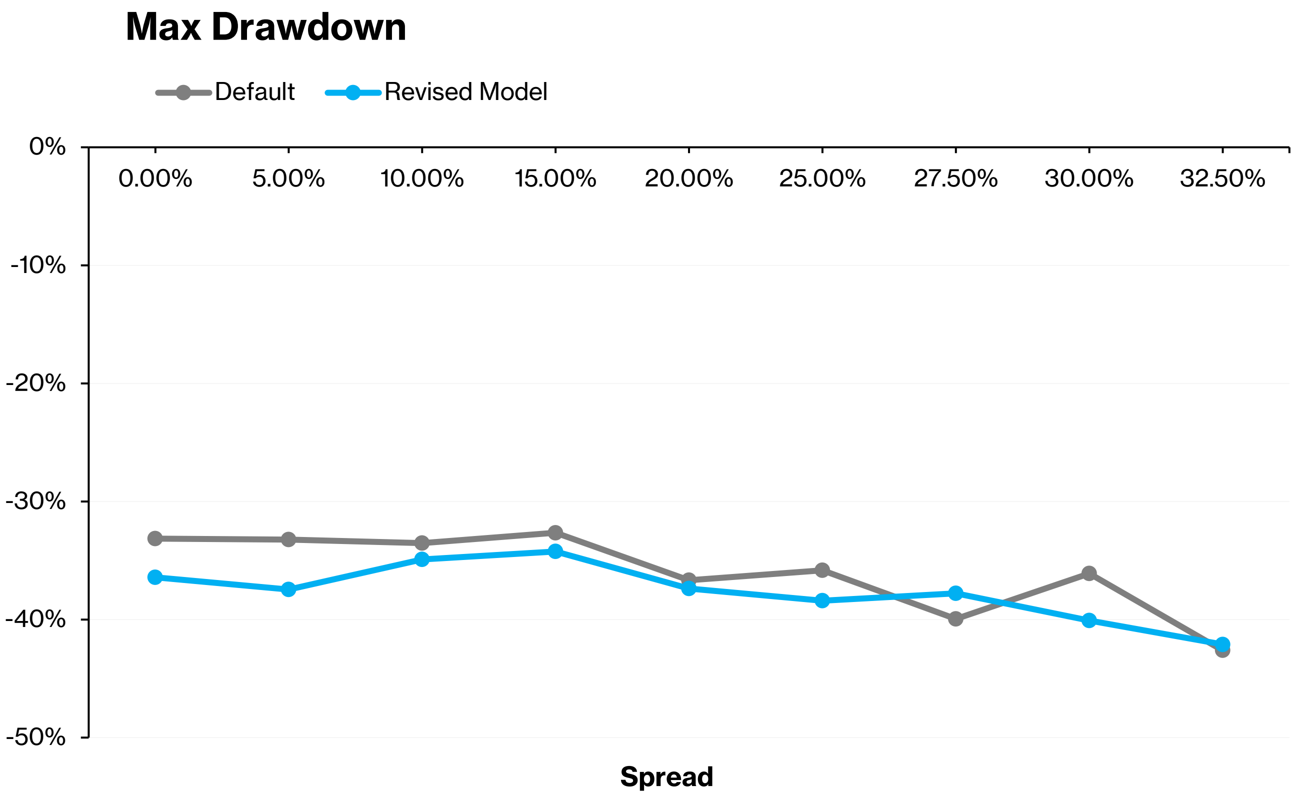



**Figure 4:** Maximum drawdowns for Baseline (Default) model versus Revised model across different spreads (or aggressive profile)

## References

Engle, R. (2002) “Dynamic conditional correlation – a simple class of multivariate GARCH models”, *Journal of Business & Economic Statistics*, 20 (2002), pp. 339-350