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Risk Modelling in Times of Crisis

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Abstract

Financial market states of high volatility in bear markets are often characterized by an increase in correlation, decreasing the diversification benefits as markets behave more homogeneously. This research focuses on the expectations of correlation and volatility across different asset classes on a risk-parity portfolio by using different measurements of risk to analyze how differently they perform, especially in times of higher volatility and correlation. This work project objective is to measure the impact of dynamically adjusting the variance-covariance matrix when such risk measures alter significantly. Moreover, a clustered risk parity portfolio will be computed with the optimal returns from the asset classes, further improving performance.

Keywords: Equal Risk Contribution, Time-Varying Correlations, EWMA

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1. Introduction

Times of crisis in the financial markets are characterized by a general decreased in prices, higher volatility of returns, and the more intense co-movements between securities increases the overall correlation levels. This work project wants to test when it is most worth to change your variance and correlation modelling by comparing the performance of four types of risk parity portfolios, each using different measurements of the same risk.

The more dynamic models to compute the variance covariance matrix often lead to more efficient portfolios, however, they also are characterized by higher turnover rates and transaction costs thus significantly reducing its benefits. With this paper the objective is to define when it is most worth to change the modelling of the variance covariance matrix and incur the transaction costs and significantly increase the returns. This comparison will be computed in three different asset classes, namely, equity, bonds, and credit.

The volatility and correlations will be used as inputs in the portfolio composition by using a risk-budgeting approach since it better diversifies risk by attributing the same percentage of the overall risk to each security versus the more traditional equal weighting method which attributes de same percentage of capital, regardless of the overall risk contribution.

The risk inputs necessary to compose a risk-parity portfolio are the standard deviation and correlation, both present in the variance covariance matrix. In this research, two types of risk-parity portfolios will be computed. Firstly, a naïve model of which only takes into consideration the volatilities, implicitly assuming a correlation of zero between the assets on the portfolio, and secondly, a "true model" which includes correlation expectations and that ensures all assets have the same contribution to the overall risk of the portfolio.

The variance covariance matrix will be computed from a backward-looking approach and a forward-looking approach. The backward-looking approach computes the standard deviation and correlation on a rolling basis giving the same weight to all observations thus making this approach less reactive to new developments, since it considers the most recent data as relevant as the oldest. The forward-looking method uses the Exponential Weighted Moving Average (EWMA) model to determine the expected volatility and correlation due to its strong performance on real data (Ding and Meade 2010). Since the EWMA is a recursive function, it better reflects the clustering in volatility and reacts more dynamically to new data.

By comparing the performance of the different portfolios by asset class, especially in times of crisis, we want to test which type of risk measurement better fits the market condition and why one should be willing to change the allocation problem of a portfolio. Furthermore, a clustered portfolio will be computed from the optimal portfolios to test the efficiency of these methodologies in a global complete diversified portfolio.

Section two is the literature review on the importance of volatility and correlation in a portfolio allocation problem and how it is not constant, as well as how dynamically approaching these metrics one can increase the performance of a portfolio. Section three and four is the data and methodology used to compute the aforementioned portfolios. Section five presents the results, and section six concludes.

2. Literate Review

Correlation between financial assets is an important factor when considering the optimally diversified portfolio. It is used across capital allocation methods and risk management as an input for the VaR computation, for example.

In standard portfolio models, correlation and volatility is assumed constant (Ang and Bekaert 2002) as in the mean-variance optimization model by (Markowitz 1952). In contrast, (Pafka and Kondor 2003) say that covariances matrixes present a high amount of noise, and the noise intensity is a function of the size of the portfolio and the length of available data and concludes that the historical correlations are not appropriate for the Markowitz optimization problem (Bhansali 2008).

Correlation is not observable and has to be estimated through observable data (Ball and Torous 2000). Moreover, there is a consensus that correlation is time-varying and tends to increase with volatility in bear markets, but not in bull markets (Longin and Solnik 2001). Additionally, the variance of returns is time-varying and can present itself in sudden spikes, thus using an *unconditional variance* is not the appropriate measure of risk for asset allocation optimizers (Solnik, Boucrelle, and Le Fur 1996) and some form of variance modelling should be considered.

This positive relationship between correlation and volatility in bear markets can be presented as financial contagion or transmission of volatility. A study on the US sub-prime crisis effects on the correlation between the American index S&P500 versus worldwide equity returns (Naoui, Liouane, and Brahim 2010) and a study of the same period focused on the cross-correlation between FTSE issues (Maskawa and Souma 2010) presented three types of financial contagion: a common shock, a spillover effect, and the pure contagion factor reflecting a behavioral component for the unexplainable market developments. Thus, correlation coefficients can be used as an indicator of the stock price sensitivity to exogenous market forces.

Using the Random Matrix Theory, a complex statistical approach to test the randomness of correlation developments (Sandoval and Franca 2012) concluded that high volatility is directly linked with strong correlations between index returns and that the distribution of correlations are not normal and present a low kurtosis in times of crisis. At the portfolio level, the tail risk is considered systematic risk according to (Bhansali 2008) and when crises happen, correlations rise in absolute value.

To solve the problem of time-varying correlation, the multivariate GARCH model Dynamic Conditional Correlation (DCC) model was created (Engle 2002) and a paper applying this approach in sector allocation (Kalotychou, Staikouras, and Zhao 2014) proved a better performance than a static model from unconditional covariance matrix although the gains from the dynamic models are significantly reduced by the higher transaction costs. Adapting portfolios to more dynamic approaches to correlations has proven to have economic value and adapting additionally for skewness and kurtosis improved performance. In order to reduce unnecessary costs, this research will analyze when is most worth to incur in these costs or continue with less costly strategies.

In times of crises and increased correlation, the diversification benefits are lowest when are needed the most, so gold will be included in order to maximize the diversity factor due to its countercyclical characteristics (Sumner, Johnson, and Soenen 2010).

3. Data

The data considered for this research is composed by securities of Equity, Bonds, Credit and Commodities asset classes and additionally Gold, between 6th of September 2007 and 11th May 2021, in order to get securities with different risk profiles.

To represent the equity asset class, the securities considered are six market-capitalization weighted ETFs of the main indexes of the US (SPY), Europe (IEV), Japan (EWJ), UK (UKX), Canada (EWC) and Australia (EWA). This assures that we are representing each region by the same weighting method, their market value, and we will compute the optimal allocation later.

For the Bond market the Futures of 10Y are considered for the same regions with TY1 for US, RX1 for Germany, JB1 for Japan, G 1 for UK, CN1 for Canada and XM1 for Australia. Regarding XM1, additional steps are needed to have a comparable set of returns by computing a synthetic price of the Future with the provided yield and adjusting for the carry and funding costs with the six months interbank overnight swap rate (AUD SWAP IOS 6M).

Regarding Credit Securities, they are separated by Investment Grade in the US (LQD US) and Europe (SPEZICET index) and High Yield Securities, HYG US and LP02TREU Index, for US and Europe, respectively. Regarding the Europe data, there are no ETFs we could work on, however the index chosen corresponds to the benchmark we wanted to include and following the transformation of adding the expense ratio we were able to obtain a synthetic ETF data series.

The data above will be used to compute the optimal returns by asset class, and then we will compute a clustered portfolio having included the commodities, for which we choose the Goldman Sachs Commodities Index (GSG) as a portfolio of different commodities, and Gold ETF is the GLD.

4. Methodology

Firstly, optimal portfolios will be computed from four different ways for three asset classes: Equity, Bonds and Credit. Secondly, using the returns from these portfolios, compose a Clustered Portfolio including Commodities and Gold.

4.1 Optimization within asset class

For the computations, all returns will be computed with equation (1), except for the XM1 where the daily carry and funding cost was included to replicate the other bond returns.

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{1}$$

For each asset class, the portfolios computed will be an equal weight portfolio, a capital-budgeting approach, and four risk parity portfolios.

A risk parity portfolio has the objective of equalizing the risk contribution from each asset, by equalizing the *marginal* contribution to the volatility of the portfolio. The marginal contribution to risk is how much the volatility of the portfolio will increase by a small change in the weight of one component. This risk-based strategy tends to limit losses from any given security, and most importantly, levels the risk between securities. Different assets have different risk profiles, and more volatile assets will be given less weight.

When building a risk parity portfolio, we need to decide if we want to always have 100% invested in the markets or if we want our portfolio to have a risk target. The risk targeting method has the advantage of when risk levels are low, the strategy dictates us to leverage and when the volatilities are increasing, we see a deleverage of the portfolio, thus better controlling risk in a time-varying volatilities scenarios. In this paper we are using a risk target of 20% for the equity portfolio, 5% for bonds and 10% for credit as they are the average volatility of the EW portfolio from each asset class. To protect from overleveraging, we added a maximum leverage of 200% to the portfolios to maintain control of transaction costs and limit risk.

The inputs required for the marginal contribution to risk are volatilities and correlations, and what distinguishes the four portfolios are the methods used to measure risk. Two portfolios will be computed with a Naïve approach to risk parity, which only considers the volatility of the assets and implicitly assumes all correlations are zero, and other two portfolios with a "true model" approach, which includes correlation expectations between the assets, besides their individual risk (a comprehensive variance covariance analysis).

For each of these portfolios the variance covariance matrix (Ω) will be computed in two different ways: A backward-looking approach, estimating volatilities and correlation from a rolling approach assuming that the recent values of these metrics are good proxies for the volatilities and correlation for the next period, and a forward-looking approach with the Exponential Weighted Moving Average (EWMA) method giving more weight to the most recent data and adapting more rapidly to times of higher volatility and correlation.

For the rolling method approach, the number of days to be considered for the computation of standard deviation and correlation will be 120 days. This value comes from the reviewed literature (Pafka and Kondor 2003) where the noise ratio of the Variance Covariance Matrix (VCV) is r=n/T, where n is the number of assets in the portfolio and T the length of data considered. Considering that the maximum number of assets in our portfolios is 6, using 120 days the noise ratio is 5%.

This value of 120 days was verified to present a lower noise by creating a series of correlated data using the Cholesky Factorization and confirming that the observed VCV was a reliable representation of the real VCV, thus making it valid to use for the rolling method computations.

Regarding the estimates of the variance and covariance in the EWMA method, the values were computed according to the formulas (2) & (3) for variance and covariance, respectively. The value of the decay factor (λ) for this research will be 0.94 as defined in RiskMetrics[1] for daily values. A small decay factor would give higher relevance to newer values, at the cost of a less persistent variance estimation. By including a decay factor on the variance modelling and covariance modelling we are creating a nonuniform weighting scheme, giving increasingly more importance to more recent data. The one exception is the first observation which was use the values of the rolling approach to start this model with an acceptable estimation of the VCV.

$$\sigma^2_{i,t+1\,|\,t} = \sigma^2_{i,t}\,\lambda + (1-\lambda) r^2_{i,t} \tag{2}$$

$$\sigma_{ij,t+1\,|\,t} = \sigma_{ij,t}\,\lambda + (1-\lambda) r_{i,t} r_{j,t} \tag{3}$$

[1] The RiskMetrics variance model is a risk management tool launched in 1994 by J.P. Morgan

Having now established how the different metrics of risk will be computed, the next step is to compute the weights for the portfolio to be in risk parity. For the Naïve method, the correlations between assets are ignored, and the optimal weights are calculated as the formula below, through a risk target:

$$w_i = \frac{\sigma_i}{\sum_{j=1}^{N} \sigma_j} \tag{4}$$

For the "True Model", the objective is to set the marginal contribution to risk from each asset equal through the equation (6) derived from equation (5).

$$\sigma_p = \sqrt{W'\Omega\, W} \tag{5}$$

$$\frac{\partial \sigma_p}{\partial w_i} = \frac{\sum_{j=1}^{N} w_i \sigma_{i,j}}{\sigma_p} = \frac{\sigma_{i,p}}{\sigma_p} \tag{6}$$

$$MCR_i = w_i \frac{\partial \sigma_p}{\partial w_i} = w_i \frac{\sum_{j=1}^{N} w_i \sigma_{i,j}}{\sigma_p} \tag{7}$$

For the rolling method portfolios, the simplified term in equation (6) can be used since we are using the historical covariance of the asset with the portfolio as the measure of risk for the next day. For the EWMA method, the expected volatility and correlation is different from the historical metrics and so, its computation is based on the longer term of the equation (6). The optimal EWMA weights are to be defined by an optimization problem computed through the *Excel Solver*, as presented in the equation below, where the marginal contribution to risk is a function of the weights, and the target marginal contribution to risk set to "1/n" of the target risk.

$$\mathrm{W}_{\mathrm{optimal}} = \min \sum \left(MCR_{target} - MCR_i\right)^2 \tag{8}$$

To sum up, the way the risk-parity portfolios will be computed can be summarized in the table below. Moving from a naïve portfolio to a rolling portfolio always increases the computations, as we include correlation expectations, and the same applies when moving from a rolling approach to a forward-looking approach since we need now to include a recursive function to determine the current forecast for risk metrics.

	Rolling Method *Backward-Looking*	**EWMA** *Forward-Looking*
Naïve	$w_i = \frac{\sigma_i}{\sum_{j=1}^{N} \sigma_j}$	$w_i = \frac{\sigma_i^{EWMA}}{\sum_{j=1}^{N} \sigma_j^{EWMA}}$
True Model	$MCR_i = w_i \frac{\sum_{j=1}^{N} w_i \sigma_{i,j}}{\sigma_p}$	$\mathrm{W}_{\mathrm{optimal}} = \min \sum \left(MCR_{target} - MCR_i\right)^2$

Table 1 - The weighting process of the four risk parity methodologies

4.2 Clustering

Having as a starting point the returns for each methodology employed to each asset class, four new portfolios are computed with the three asset classes plus commodities and gold, to create a globally optimally diversified portfolio. By including gold separately from the other commodities, we can model its correlation with other asset classes and take better advantage of its countercyclical properties discussed in the literature review.

In each portfolio the objective is to get the same level of risk for each of the five asset classes, and this can be achieved by setting the marginal contributions to risk equal, by the same process discussed previously. However, for the clustered portfolio the risk target is 10% which is the average standard deviation of the clustered equally weighted (EW) portfolio, a portfolio attributing the same weight to the four asset classes and gold. With a risk target of 10% and five securities in the portfolio, each should have a risk contribution of 2%. To maintain the same approach to leverage, it will be limited to a maximum of 200%.

A clustered portfolio is a portfolio composed of already optimized portfolios, in this case, a global portfolio composed of the optimal asset classes' returns. A clustered equal weight, a clustered rolling naïve portfolio, a clustered rolling "True model" and a clustered "True model" EWMA are computed using the same weighting process used to derive the corresponding asset class returns.

5. Results

The results from this research will first be analyzed on the asset class level, as the behavior of the parameters of the variance covariance matrix (VCV) is not equal between asset classes and so, the four risk parity portfolios will be analyzed on how differently they perform depending on their assumptions of the VCV. The backward-looking methods use historical values and attribute the same weight to each observation, thus making it a sensible strategy if the VCV is more static. However, variances and correlations are time-varying and if the market changes to a state of higher volatility and correlations suddenly, inaccurately determining the VCV can lead to lower returns compared to more reactive and dynamic modelling of the VCV as the forward-looking portfolios do.

From literature (Longin and Solnik 2001) we learned that states of high volatility tend to be followed by a high correlation only in bear markets, while in bull markets the increase in correlations is not significant. So, to compare the performance of the portfolios in the moments when losses are larger, a post-hoc analysis will determine when the highest volatilities and highest correlations happened simultaneously, and these periods we will call times of crisis.

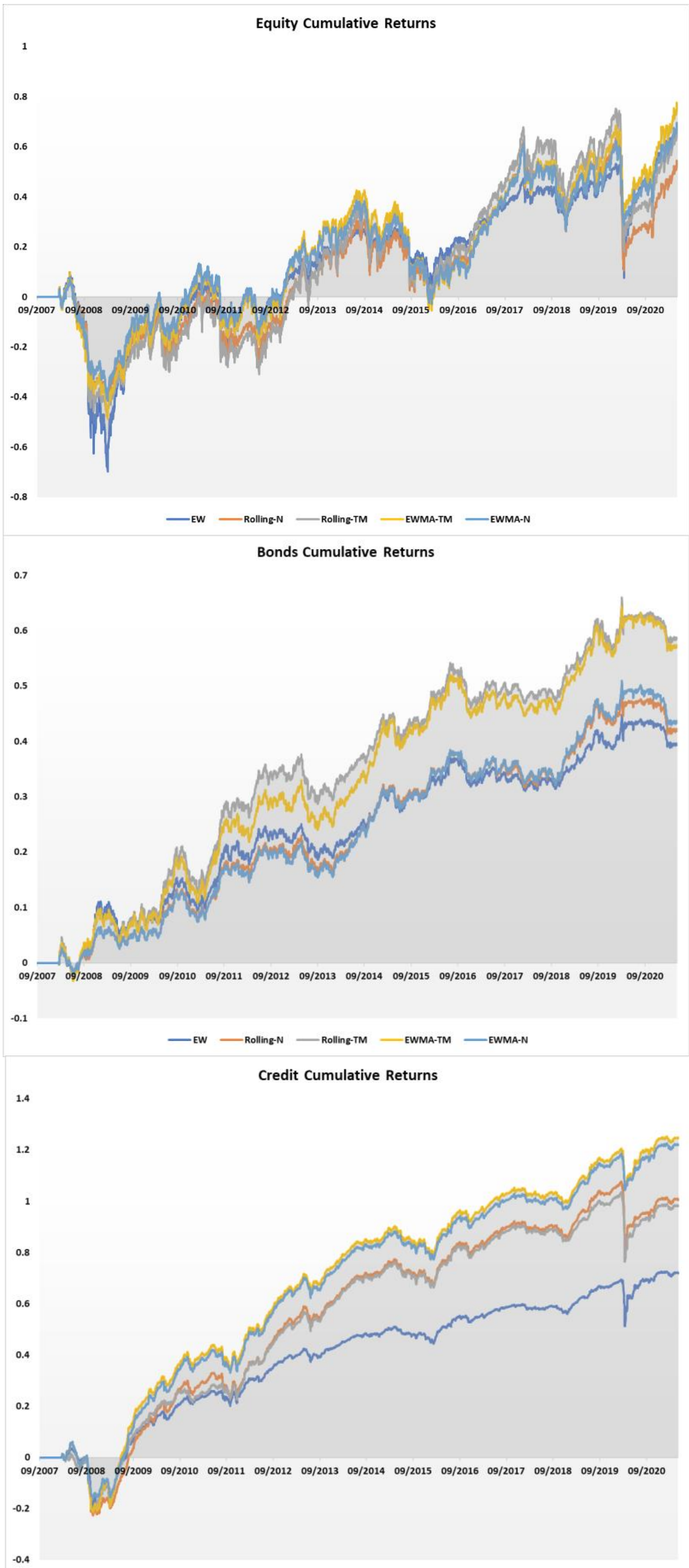
For this we first need to decide how to measure the immediate general levels of volatility and correlations to then determine when they are high. For this purpose, the daily average of the inputs of standard deviation and correlation from the EWMA were used, due to its quicker reaction to new data, creating a better indicator of sudden moves in the VCV. The thresholds to be considered in high levels for the volatility or correlation differ between asset classes as it depended on the distribution of these metrics, but times of crisis should reflect less than 10% of all the trading days.

Since the objective of this research is to determine when it is best to switch the risk modelling approach to compose a portfolio, we are comparing the returns across all data, and focusing then on times of crisis by comparing conditional returns, meaning, comparing the returns of the risk parity portfolios only if they were in times of high volatility and high correlation. The reason not to employ the more dynamic model constantly is due to the much high turnover of the portfolio, translating to higher transaction costs. Risk parity portfolios that take correlation into consideration also present a higher turnover than Naïve models due to more changing inputs.

Lastly, the performance of the clustered portfolios will be analyzed to see how the expectations of the correlations between asset classes and gold affect performance of a globally diversified portfolio.

5.1 Asset Classes

The Equity portfolios are very similar in terms of cumulative returns (*Graph 1*), although we can see a slight overperformance of the EWMA approach and the "True Model"(TM) – which includes correlation expectations. This is also shown in *Table 2*, as the Info Sharpe (IS) from the EWMA portfolios were higher than the rolling portfolios, and the IS from the "True Models" were higher than the Naïve models, although having a higher volatility. In *Table 3*, we are computing the difference in returns from different portfolios. Firstly, we can see that the excess return from the Rolling "True Model" compared to the Rolling Naïve that the cost



Graph 1 - Risk parity portfolios cumulative returns by asset class of not including correlations amounted to an average of 0.88% annually in lost returns. However, if we were already using the Rolling "True Model", we could get an additional 0.75% annual return by changing our weighting method to a more dynamic one (EWMA-TM). This value proves that there is economic value in adding correlations expectations in the equity asset class, as well as that the VCV can be more dynamic than assumed in the backward-looking approach.

Considering only the days when the average daily volatility was above the 85th percentile, the high volatility states, the returns for the EW was -6.87%, while the rolling portfolios had these conditional returns lower than -20% (*Table 4*). On the other hand, the EWMA portfolios had about half the losses from the EW. When the volatility increased, the rolling methodology was too slow to adapt to a different market state, because it still considers a large amount of data with an outdated volatility expectation. When correlation levels were at the highest levels, we can see the better performance from the EWMA-TM versus EWMA-N, because it takes the correlation expectation into consideration.

		Rolling		EWMA	
Equity	**EW**	**Naive**	**True Model**	**Naïve**	**True Model**
Av Return	4.87%	3.82%	4.70%	4.90%	5.46%
Standard Deviation	20.51%	18.52%	20.99%	17.59%	19.89%
Info Sharpe	0.237	0.206	0.224	0.278	0.274
Maximum Drawdown	-79.73%	-52.75%	-56.96%	-49.48%	-58.52%
Annual Turnover		221%	323%	993%	1272%

		Rolling		EWMA	
Bonds	**EW**	**Naive**	**True Model**	**Naïve**	**True Model**
Av Return	2.87%	3.06%	4.27%	3.16%	4.16%
Standard Deviation	3.96%	3.63%	4.76%	3.69%	4.78%
Info Sharpe	0.726	0.843	0.898	0.857	0.872
Maximum Drawdown	-6.52%	-8.06%	-9.07%	-8.00%	-9.00%
Annual Turnover		213%	625%	1018%	1448%

		Rolling		EWMA	
Credit	**EW**	**Naive**	**True Model**	**Naïve**	**True Model**
Av Return	5.26%	7.35%	7.16%	8.90%	9.10%
Standard Deviation	5.25%	5.44%	5.20%	4.73%	5.21%
Info Sharpe	1.001	1.350	1.378	1.881	1.746
Maximum Drawdown	-24.68%	-28.16%	-27.13%	-21.89%	-27.41%
Annual Turnover		314%	834%	1149%	1398%

Table 2- Portfolio Performance by Asset Class

The days when these two restrictions occurred simultaneously, defined previously as times of crisis, the EW portfolio had a loss of 13% while the EWMA portfolios had half of the losses, showing it is a good methodology to reduce drawdowns. In the Bonds portfolios, the biggest difference in cumulative returns came from the "True Models" adding to the benefits of increasing correlation metrics in portfolio allocation problems. From *Table 3*, the additional return for including the correlation expectation in the weighting process was 1.2% for the Rolling method, and 1.0% for the EWMA. The drawdowns are very similar within the "True Models", of around 9%, and the Naïve portfolios, of around 8% (*Table 2).* In this asset class there is no clear overperformance in times of crisis of any methodology in particular, and since there is no clear advantage from moving from the Rolling approach to the EWMA, the volatility and correlation metrics in this asset class appear to be stable, at least for our timeframe, and making the rolling approach more attractive as it has less transaction costs due to turnover.

Equity Excess Returns	**Rolling (TM - N)**	**EWMA (TM-N)**	**TM (EWMA-Rolling)**
Av Excess Return	0.881%	0.562%	0.755%
Total Excess Return	12.050%	7.687%	10.333%
Maximum	1.38%	0.80%	6.44%
Minimum	-1.37%	-0.91%	-4.22%

Bonds Excess Returns	**Rolling (TM - N)**	**EWMA (TM-N)**	**TM (EWMA-Rolling)**
Av Excess Return	1.212%	1.000%	-0.107%
Total Excess Return	16.587%	13.688%	-1.469%
Maximum	0.63%	0.52%	0.71%
Minimum	-0.65%	-0.79%	-1.32%

Credit Excess Returns	**Rolling (TM - N)**	**EWMA (TM-N)**	**TM (EWMA-Rolling)**
Av Excess Return	-0.181%	0.097%	1.835%
Total Excess Return	-2.483%	1.334%	25.109%
Maximum	1.16%	0.94%	3.12%
Minimum	-1.10%	-1.31%	-1.54%

Table 3 - Comparing Portfolio returns

Regarding the Credit portfolios, we can see that the cumulative returns are in groups, the EW portfolio with the lowest cumulative return and the EWMA portfolios are the highest. In these portfolios, the biggest gain can be attaining from moving from a Rolling approach to the EWMA in the "True Model", adding on average 1.84% annually (*Table 3*). This leads us to believe that this is the most dynamic VCV so far as the rolling approach, by looking at historical values, has much lower predictive power in this asset class. The biggest gains in the EWMA come from the reduced drawdowns in times of crisis, where the return from the EW is 3.55% while the EWMA-TM is 9.97%.

Equity Conditional Returns	**EW**	**Rolling-N**	**Rolling-TM**	**EWMA-N**	**EWMA-TM**
Volatility, Top 15%	-6.87%	-21.02%	-23.17%	-3.61%	-3.39%
Correlation, Top 15%	4.56%	-17.14%	-20.43%	9.93%	10.83%
Both	*-13.14%*	*-28.56%*	*-31.89%*	*-7.05%*	*-7.50%*

Bonds Conditional Returns	**EW**	**Rolling-N**	**Rolling-TM**	**EWMA-N**	**EWMA-TM**
Volatility, Top 20%	14.17%	9.70%	14.65%	8.85%	12.97%
Correlation, Top 30%	9.27%	12.05%	13.31%	13.12%	16.14%
Both	*-0.68%*	*-0.96%*	*-1.45%*	*-0.68%*	*-0.70%*

Credit Conditional Returns	**EW**	**Rolling-N**	**Rolling-TM**	**EWMA-N**	**EWMA-TM**
Volatility, Top 25%	24.23%	15.75%	20.53%	35.39%	41.06%
Correlation, Top 40%	22.74%	30.85%	36.20%	44.25%	44.66%
Both	*3.55%*	*-2.86%*	*2.50%*	*9.20%*	*9.97%*

Table 4 – Returns in times of crisis

In all asset classes volatility or correlation expectations impact results from different ways, due to different variance covariance matrix behaviors and our assumptions. If the variance covariance matrix is more static as in the bond market the biggest gain for a risk parity portfolio is to include the correlation expectations. On the other hand, if the variance covariance changes are more dynamic, like in the credit portfolios, a constant adjustment to the VCV is desirable.

5.2 Clustered Portfolio

The clustered portfolios used the optimal returns computed from each asset class and constructs a global risk parity portfolio, diversified within asset classes through different regions and on the global level by using different asset classes in its composition. To achieve this we use the same methodology used to compute the respective optimal asset returns. In doing so, we expect to create an increasingly efficient diversified portfolio by including correlations on the risk parity portfolio construction and measure how differently the results are if we only consider the EWMA returns, computed for each asset classes, instead of the rolling portfolios.

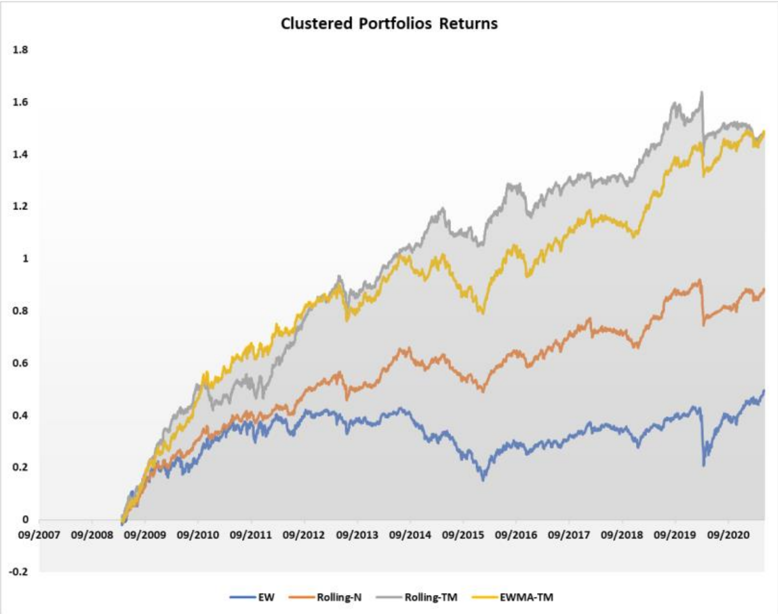
The cumulative returns from the clustered portfolios are presented in *Graph 2*, where the Rolling-N is superior to the EW.

Additionally, the True models overperform the naïve portfolio, and have a much higher IS, as the Rolling-N has an IS of 1.16 versus an IS of 1.51 of the Rolling-TM and 1.41 of the EWMA-TM (*Table 5)*.

Clustered Portfolios	EW	Rolling-N	Rolling-TM	EWMA-TM
Av Return	2.34%	6.99%	11.80%	11.78%
Standard Deviation	9.47%	6.03%	7.84%	8.35%
Info Sharpe	0.248	1.161	1.505	1.411
Maximum Drawdown	-27.80%	-17.86%	-24.47%	-22.90%

Table 5 - Clustered portfolios performance

This IS values are much higher than the portfolio computed for the asset classes, except for Credit portfolios. The origin of this increase in IS can be because we are already using the portfolios with higher returns as inputs in this new portfolio as well as benefiting now from the correlation between asset classes, instead of only within asset classes. Although these returns seem close, the superior cumulative turnover costs of the EWMA portfolios could significantly reduce any overperformance.



Graph 2 - Cluestered portfolios cumulative returns

6.Conclusions

In this research the initial objective was to analyze when it was more worth to change the variance covariance modelling in a risk parity portfolio, to adapt for any changes in the general levels of risk present in the variance covariance matrix and create a more efficient portfolio.

More dynamic approaches to the variance covariance modelling were expected to overperform less dynamic ones, like the rolling method. This was the case for the credit asset class, as the VCV is more volatile. However, this was not the case for the bonds, where the variance covariance appears to be much more static, thus, only including correlation significantly improved results as they are more suitable to be used as a proxy for the unobservable correlations. Here we can conclude that the performance of the models depends on the real VCV time-varying component, and that they vary by asset class.

When considering times of crisis, the more reactive models were always better, or equal, but never worst, thus proving that volatilities and correlations could be used to define a regime switching strategy to change between risk parity weighting methods. This was to be expected, as we are already restricting our analysis period to times of crisis which is already a diversion from the mean.

From the clustered portfolios, we get a much higher Info Sharpe from any individual asset class, proving that this method is very efficient to approach a complete global risk parity portfolio, and quickly adapts to times of crisis.

The conclusion of this work project is that volatility and correlation can be used as an indicator of times of crisis, and to determine which is the better risk modelling approach depends on the variance covariance profile of each asset class and the current market state.

Further research could be done on the distribution of correlation through time, to model the variance covariance in a more definitive way. Furthermore, this type of correlation analysis could be extended to different types of assets as they could provided new sources of diversity.

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