Quality in Times of Insanity: a Study of Quality Factor Investment Strategies in Stressed Markets

Master Thesis

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Abstract

This thesis explores the flight-to-quality phenomenon in financial markets and investigates systematic equity investment strategies using a quality style factor to achieve portfolio resilience and potentially outperform the market during periods of stress.

The findings first highlight the existence of a quality factor portfolio that exhibits a negative correlation with the market, particularly during challenging market conditions. Thereafter, indicators with significant correlations to market returns and an inverse relationship with the quality factor portfolio are identified. Finally, we show that using these indicators to uncover two distinct market regimes with varying risk profiles and switching between the market portfolio and the quality factor yields superior risk-adjusted returns than the two portfolios alone.

This research offer insights for risk management and portfolio optimization, providing financial practitioners with strategies to navigate market turbulence effectively. However, limitations such as the specific dataset used and the assumption of stationary market dynamics should be considered. Further research can refine the selection of quality metrics, explore additional indicators and investigate regime detection methodologies more thoroughly to enhance the applicability and robustness of the findings.

Keywords: Factor Investing, Quality Factor, Financial Stress Indicators, Regime Switching, Asset Allocation

JEL Classification: G10, G11, G15

Cette thèse explore le phénomène de fuite vers la qualité sur les marchés financiers et étudie les stratégies systématiques d'investissement en actions sur la base du facteur de qualité pour apporter de la résilience et potentiellement une surperformance au portefeuille par rapport au marché durant des périodes de stress financier.

Tout d'abord l'existence d'un portefeuille comprenant des actions d'entreprises ayant des charactéristiques de haute qualité qui présente une corrélation négative avec le marché, en particulier lorsque les conditions de marché sont difficiles est mise en évidence. Ensuite, des indicateurs présentant des corrélations significatives avec les rendements du marché et une relation inverse avec le portefeuille de facteurs de qualité sont identifiés. Enfin, ces indicateurs sont utilisés pour déterminer deux régimes de marché avec des profils de risque distincts qui permettent de choisir entre le portefeuille de marché et celui du facteur de qualité mène a des rendements ajustés au risque supérieurs aux deux portefeuilles.

Cette recherche offre des perspectives pour la gestion des risques et l'optimisation de portefeuille durant des périodes de turbulences du marché. Toutefois, il convient de tenir compte de certaines limites, telles que l'ensemble de données spécifique utilisé et l'hypothèse d'une dynamique de marché stationnaire. Des recherches supplémentaires peuvent affiner la sélection des mesures de qualité, explorer des indicateurs supplémentaires et enquêter sur les méthodologies de détection des régimes afin d'améliorer l'applicabilité et la robustesse des résultats.

Contents

1 Introduction

With large rate increases in response to spiralling inflation, the Ukraine War-linked energy crisis in the EU and real estate market issues in China to name just a few recent events, market instability is rife. In response, many investors have taken a more defensive stance with their strategies by moving to safer assets, a phenomenon often called flight-to-quality.

In finance, flight to quality refers to the tendency of investors to move funds to safer, higher-quality assets, which are expected to be more stable in value, in times of financial stress according to Hakkio and Keeton (2009). This can occur in times of economic uncertainty, market volatility, or when there are concerns about the future of a particular asset class.

To make these purchases, riskier assets, such as stocks or high-yield bonds are sold leading to a decrease in their prices and inversely, an increase in the price of safer assets as shown in Prendergast (2009). Furthermore, Bernanke et al. (1994) show that it can lead to an increase in the cost of capital which can exacerbate economic instability and have a significant impact on financial markets. They can lead to lower stock prices, higher bond yields, and a decline in the value of other risky assets. In some cases, they can even lead to a financial crisis.

Oftentimes, investors seek out assets such as government bonds as discussed in Durand et al. (2010) because they are considered to be among the safest investments thanks to their backing by the issuing government. Other safe-haven assets can include precious metals, most commonly gold, which has a long history of holding its value over time, or also exposure to certain currencies such as the Swiss Franc or the Japanese Yen.

However, not all investment managers have the luxury of moving funds between different asset classes. Indeed, the manager of an equity fund can only purchase stocks. If he is lucky, his mandate might allow for some cash but there is rarely enough leniency to have a significant impact on asset allocation. This might explain why there is also evidence that a flight to quality can occur in equity markets (Ferrante-Bannera and Sandøy, 2021). In fact, during times of market stress or uncertainty, investors appear to seek out stocks that are less sensitive to negative economic conditions, which is aligned with the finding of Monin (2019) that financial stress can be a precursor to declining economic activity.

One of the most prominent methods to reduce risk in a stock portfolio is to invest in sectors such as healthcare, utilities, and consumer staples as these sectors are generally less cyclical, meaning that their performance is less closely tied to the overall state of the economy. The downside to this strategy is that it can lead to a decrease in diversification which in itself is an added risk.

For this reason, this paper will explore a different approach. Instead of being limited to just a few defensive industries, we will explore a variety of systematic equity investment strategies based on the quality factor which could offer portfolio resilience and hopefully even outperformance through difficult market conditions such as those observed recently.

Devising investment strategies that benefit from the flight-to-quality phenomenon poses three challenges. Firstly, one must be able to identify which traits investors deem to be of higher quality and which are therefore sought after when moving to safety. Secondly, conditions which trigger market participants to seek refuge must be found. Finally, we must determine how to capitalize on the phenomenon. Thankfully these questions are the subject of extensive research.

To define quality, we will identify various company-specific metrics which financial literature describes as being indicators of quality in hopes of finding well-managed businesses with strong fundamentals which should be capable of weathering a storm. The methodology of the Quality Minus Junk (QMJ) factor developed by Asness et al. (2019) will be closely followed, meaning that we will take a factor investing approach.

To predict flights to quality, we will examine various commonly used financial indicators as well as some composite ones created by financial authorities and select the ones which are correlated to market returns and inversely correlated to those of the quality factor.

Finally, to reach the ultimate objective, which is to benefit from the flight-to-quality phenomenon dynamically, we use the selected indicators to identify two separate regimes, one of market stress where the quality portfolio performs better than the market and one of market stability where the market does better. This will allow us to build an investment strategy where we switch between holding the market portfolio and the quality one depending on the regime. We implement three different strategies to ascertain the regime from the indicators. Initially, a simple rule-based method is used, then k-Means clustering and finally a Hidden Markov model (HMM).

2 Defining quality

2.1 Quality in Financial Literature

There is no consensus on the definition of quality although Asness et al. (2019) vaguely defines quality as "characteristics that investors should be willing to pay a higher price for". Hsu et al. (2019) on the other hand observe seven salient characteristics underpinning most definitions. These are balance sheet strength, earnings stability, growth in profitability, profitability, accounting quality, payout, and investment conservativeness. Their research concludes that only the 4 last elements constitute sizeable premia whereas the others mostly fit within a storytelling or marketing perspective and seem like perfectly reasonable measures of quality on the surface.

What is more, there are several approaches to investing in high-quality companies. For example, Warren Buffett and Charlie Munger, sift through annual reports in search of strong fundamentals and solid business models which, over time, are expected to offer good returns on investment and stability.

For the purposes of this paper, however, a more systematic approach will be taken to select stocks which is called factor investing. This field of finance has been spawned by the desire to predict asset behaviour by identifying characteristics or factors, that drive asset risks and returns. Within this school of thought, two categories of factors can be discerned. The first one groups macroeconomic factors, such as interest rates, inflation and economic growth, that have an impact across asset classes. They generally have a straightforward link to company valuations be it through impacting revenues, costs or the ability to raise capital to give some examples. The other category and the one of interest in our definition of quality, is comprised of so-called style factors which characterize drivers within asset classes, with the largest body of work concentrated on equities. This type of factor can be much more subjective and its relation with asset performance much more convoluted. Their subjectivity is such that all types of metrics have been used to leading Feng et al. (2017) to coin the term factor zoo.

The emergence of style factors can be traced back to the Capital Asset Pricing Model (CAPM) introduced by Treynor (1961) which posits that stock returns are proportional to the amount of systematic risk borne by said stock implying the presence of a market factor. In the years following, multiple new factors were discovered to have a statistically significant correlation with stock returns. The most notable major milestone in terms of factor models emerged decades later through the Fama and French (1992) 3-factor model (FF3) supplementing the CAPM with 2 new factors, Size, which captures the outperformance of companies with small and medium market capitalizations compared to those with larger ones and Value which harnesses the outperformance of inexpensive stocks versus expensive ones. Another notable model is the Carhart (1997) four-factor model which supplemented FF3 by considering Momentum, the tendency of performance to persist. Finally the Fama and French (2015) 5-factor model (FF5) builds upon its predecessor, the FF3, by considering the robustness of profitability as well as the conservativeness of a company when it comes to investing. These two new factors in particular are of great interest to this paper since they align with some definitions of quality investing.

Part of the reason for this lack of consensus is the limited understanding of the rationale behind the premium. Most factors can either be categorized as being deserving of a premium due to the additional risk they entail, this is the basis for the CAPM for instance. Other times, the empirical outperformance of factors is due to less straightforward phenomena such as behavioural bias. Chen et al. (2021) argue this is the case for the momentum factor for example.

In the case of quality, it seems like common sense that the characteristics are desirable and therefore that no outperformance is warranted. However, in their study of the low-volatility anomaly Baker et al. (2011) posit that behavioural biases bid up risky investments more than what is warranted whereas investor constraints limit pricing anomaly corrections. Quality is perhaps seen as too boring and without an attractive upside potential.

2.2 Building our Quality Factor

2.2.1 Data Description

To construct our quality factor, close to 20 years of company-specific data were collected between the October 30th 2002 to September 9th 2022. The companies taken into consideration are the constituents of the MSCI World Index which, over the aforementioned time span, amount to 3387.

From a geographical standpoint, 42 countries across 5 regions are represented and we observe in fig. 5 a heavy bias toward the United States. Regarding the activity of the companies, the distribution across the 11 Global Industrial Classification Standard (GICS) sectors paints a similar picture, albeit less drastic with financials hoarding the most market value (see fig. 6)

The metrics collected aim to represent the multi-signal nature of quality and can be categorized under the 4 sub-factors Hsu et al. (2019) identify as having statistically significant premia. table 1 through table 4 show the metrics used to construct the factor as well as their observation frequency and whether they are positively or negatively associated with quality.

Profitability			
Variable	**Description**	**Freq.**	**Relation**
ROE	Trailing 12-month Return on Equity	Monthly	Positive
ROA	Trailing 12-month Return on Assets	Monthly	Positive
COGSoS	Cost Of Goods Sold over Sales	Quarterly	Negative
PM	Net Profit Margin	Quarterly	Positive

Table 1

Accounting Quality			
Variable	**Description**	**Freq.**	**Relation**
SoR	Sales over receivables	Quarterly	Positive
CFOtoNI	Cash Flow from Operations to Net Income	Quarterly	Positive

Table 2

2.2.2 Constructing our Factor Portfolio

Looking at the descriptive data of these variables in table 9 to table 20, we observe a high degree of heterogeneity. Indeed, we are comparing accounting metrics and ones from

Payout			
Variable	**Description**	**Freq.**	**Relation**
DIss	Debt Issuance	——-	Negative
EIss	Equity Issuance	——	Negative

Table 3

Investment			
Variable	**Description**	**Freq.**	**Relation**
CapExonDnA	Capital Expenditures over Depreciation and Amortization	Quarterly	Negative
gA	Growth in Assets	——-	Negative
gCapEx	growth in Capital Expenditures	——	Negative

Table 4

financial markets which have different observation frequencies and scales. Comparing them as they are makes no sense. We must therefore normalize the data to be able to combine them first into the 4 sub-factors and later into the quality factor. Another issue with this data is the high degree of variability caused by outliers. To resolve these two issues, we apply the z-scoring methodology from Asness et al. (2019).

Firstly, we compute the cross-sectional z-score of the variable's rank for company n at period t for each of the 12 variables x as follows:

$$z_{x_{n,t}} = \frac{Rank(x_{n,t}) - \mu_t}{\sigma x_t} \tag{1}$$

$$\mu_{x_t} = \frac{\sum_{i=1}^{N} Rank(x_{i,t})}{N} \tag{2}$$

$$\sigma_{x_t} = \sqrt{\frac{\sum_{i=1}^{N} (Rank(x_{i,t}) - \mu_{x_t})^2}{N}} \tag{3}$$

where:

N = The number of companies, here 3887

$Rank(x_{n,t})$ = The cross-sectional rank of variable x for company n

Now, we can see in table 21 to table 32 data behave much more similarly since computing the z-scores has the effect of normalizing the different variables which then allows them to be compared and combined whereas using the ranks of the values instead of the values themselves removes the biases which would result from outliers such as having a very large σ_{x_t} for example. One could also approach the issue of outliers through winsorization, whereby values within the top and bottom p percent of data would be replaced by the top and bottom p^{th} percentile respectively. This would have the effect of preserving some of the characteristics of the variables' distributions which could be of use. In our case, however, we are primarily interested in the order of the values which is why using ranks will suffice.

Next, we add an intermediate step in order to analyze each of the sub-factors of quality. We do this by summing the relevant $z_{x_{n,t}}$ for each of the sub-factors times 1 or -1 depending on the direction of the relation and compute the z-score on the results of the previous operation for each sub-factor in the same manner as for the initial variables to find $z_{subfactor}$. This prevents sub-factors which are composed of more metrics to be given an unfair bias when combined with the other sub-factors.

For instance, to get the Profitability sub-factor z-scores, we compute:

$$Profitablity = z(z_{ROE} + z_{ROA} - z_{COGSoS} + z_{PM}) \tag{4}$$

Finally, for the Quality z-scores, we add all the sub-factors together and again compute the z-score over the ranks as so:

$$Quality = z(Profitability + AccountingQuality + Payout + Investment) \tag{5}$$

Further research could be done on the way the sub-factors or even the initial financial metrics are weighted when merged given the various information they each contain. Indeed, not all these factors are created equal and what is more could imagine using equal risk contribution as in Maillard et al. (2010) for example to weigh the different facets of Quality.

The result of these data transformations is in one T by 3387 shaped matrix of z-scores for each of our 12 financial variables, 4 sub-factors and the quality factor, with T varying depending on data frequency.

To build portfolios out of these matrices, at each rebalancing date, we will go long the companies which appear in the top 30% of values and short the bottom 30% as in Fama and French (1992). For the purposes of a sensitivity analysis, a range of percentile values are evaluated in the code but to remain concise, the 30% cutoff percentile is retained and the other versions will not be explored for investment strategies. There is certainly work to be done in optimizing the percentile value with regards to trading costs for example, or even dynamically adapting the cutoff percentile to express one's outlook on quality stocks. Having selected the direction of the trade, we weigh the positions proportionally to the market capitalization of each stock in order to avoid extreme tracking errors.

It is noteworthy that, on the one hand, the z-scores are market-cap agnostic, which means that each company has an equal impact on the components of the z-score formula. Hence the relative quality of a stock has no in-built bias towards any industry or location except due to the number of companies available. On the other hand, the portfolio will be heavily exposed to geographical and industry biases due to the cap-weighting aspect.

Observing the resulting distributions across countries of the quality cap-weighted long-short portfolio in fig. 7 we notice a large net overweight in US stocks which is surprisingly sourced from a net negative position from Japan, Germany and France. Diving deeper into the sub-components of our factor, we notice the same phenomenon in the profitability portfolio in fig. 13. This could be due in part to the finding of Blaine (1994) that it is difficult to compare financial metrics across countries due to the different tax regimes and accounting standards. This means that we are perhaps unjustly dismissing Japanese and German companies purely because we have chosen US-centric measures of profitability.

Concerning the weight distribution on a sector basis, fig. 10 expresses a weariness of the financial sector. Parsing through the sub-factors, the conclusion is more nuanced, however as Profitability and Accounting Quality both weigh the sector down whereas Investment is heavily bullish on the sector. Looking at the portfolios which would result from the individual metrics, although the CapEx to DnA ratio is advantageous, and results in a close to 25% net long weight, due to the nature of their assets, ROA gives a considerable net short weight of close to 50%. This is not much of a surprise given the atypical balance sheets and business models of the banks, and insurance companies which comprise this sector. Again, comparability across industries is not always straightforward and special considerations are normally made for financial institutions on many accounting metrics.

To avoid unjust discrimination between countries or sectors or to limit tracking error, (i.e. to remain sector and country neutral), a solution would be to normalize the financial metrics on a country-by-country, sector-by-sector basis or both before they are standardized as a whole to be then aggregated with other metrics. In our case, however, we will continue with the unconstrained version of quality

2.2.3 Observing the Performances

Having determined the proportion of capital to allocate to each company at each period, we can now compute the performance of the portfolio. Since we intend to derive investment strategies from unsupervised models, we evaluate the returns of each portfolio over the in-sample period which will be used as a training set and which represent the first 70% of periods. The other 30% will later be used to test how robust the models are over out-sample period. Our time frame of interest, therefore, spans from 2002-10-11 to 2016-10-10

At first glance, observing the cumulative returns of our portfolio in fig. 1 might be somewhat disappointing. However, looking at the scatter plot of returns, in fig. 2 as well as the performance metrics in table 6 we realise that our portfolio is what we are looking for. Indeed the fact that it is generally defensive as shown by the values for volatility, downside volatility and maximum drawdown, means it could already offer an interesting alternative to the benchmark during periods of high volatility for risk-averse investors. Moreover, the negative beta, Pearson and Spearman correlation coefficients and the negative slope between the returns of the portfolio and those of the benchmark tell us that the portfolio is negatively correlated with the benchmark throughout the time frame and that it could be a good investment if our outlook on the benchmark is negative, if we are expecting the market to crash for example. The relatively low Downside Capture Ratio tells us that the negative correlation is also present when it counts and supports the idea that owning high-quality stocks is beneficial when the benchmark is in decline.

Nevertheless, the Sharpe, Information and Sortino Ratios show us that it is not all roses and that there is certainly value to be created if we are able to determine when to switch between the market portfolio and the quality one, i.e. when flights to quality occur.

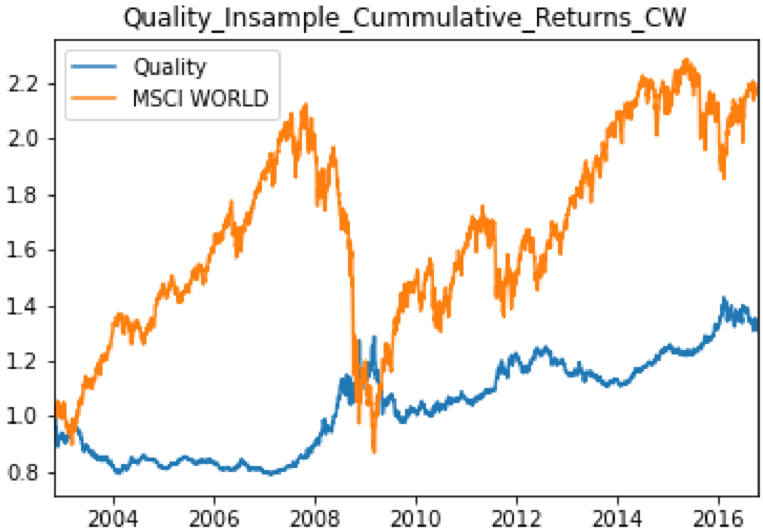

Figure 1

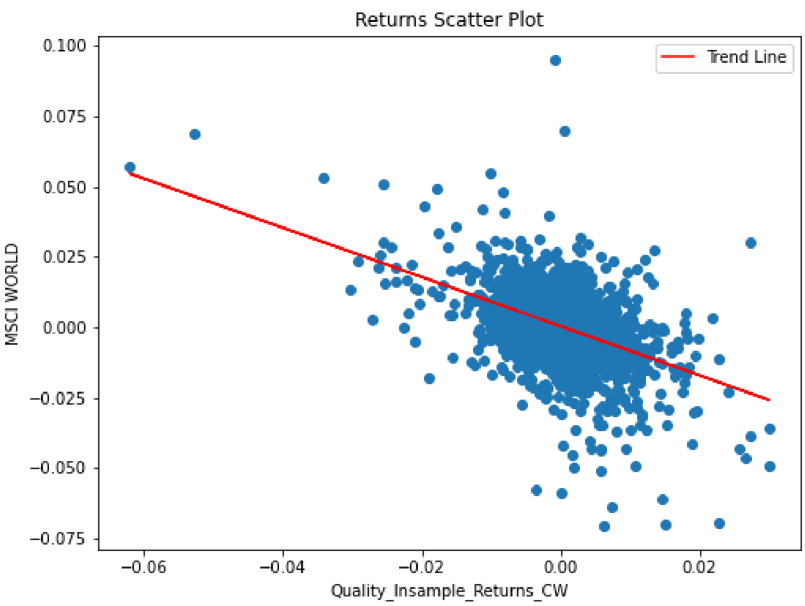

Figure 2

	MSCI World	Quality_Results_CW
Annualized_total_return	0.06	0.02
Volatility	0.16	0.08
Downside_volatility	0.10	0.05
Sharpe_Ratio	0.33	0.10
Informaiton_Ratio	NaN	-0.21
Sortino_Ratio	0.50	0.15
Beta	1.00	-0.23
Pearson_Correlation	1.00	-0.45
Spearman_Correlation	1.00	-0.38
Max_Drawdown	0.59	0.24
Hit_Ratio	0.54	0.51
VaR_95%	0.01	0.01
Expected_Shortfall_95%	0.02	0.01
Downside_capture_ratio	1.00	-0.25

Table 6

3 Detecting Financial Stress

In a similar vein as for the quality factor, there is not one single indicator or definition of financial stress. Nevertheless, Hakkio and Keeton (2009) have identified five as symptoms of financial stress: Uncertainty about the fundamental value of assets, uncertainty about the behaviour of market participants, information asymmetry buyers and sellers of securities, desire for liquidity, and most relevant of all, desire for less risky assets, also known as a flight-to-quality. Due to the complexity and interconnectedness of financial markets, abnormal market behaviour can originate from a multitude of different sources, sometimes at the same time and as such, the indicators most commonly monitored by market participants are diverse as seen in Kliesen et al. (2012).

3.1 Standalone Indicators

Events in credit markets such as the FED's rate hiking affect financial markets as a whole since the relative attractiveness of fixed income assets is made greater. It also impacts equity valuations through the increase of the discount rate. When equity markets experience periods of heightened volatility, investors may become nervous about potential losses and purchase assets with less drastic price swings. Concerns about the creditworthiness of companies or the overall stability of the financial system, investors may become more risk-averse. They may sell their equity holdings, especially those of companies with higher levels of debt or weaker financial positions, and seek safer assets to protect their capital. This is why some definitions of quality intend to capitalize on this phenomenon by including measures of balance sheet stability.

One of the most commonly used indicators of investor sentiment for equity markets is the Chicago Board Options Exchange's Volatility Index (CBOE VIX), sometimes nicknamed the Fear Index. It extracts the short-term implied volatility of the S&P 500 index using options with a 30-day maturity. Munenzon (2010) outlines that the performance of equities is sensitive to the level of the VIX in that "the percentage of positive days for equities drops very quickly as VIX rises". This supposed link with stock performance makes it a promising flight-to-quality barometer.

Another popular indicator of market conditions is the term structure of interest rates, also known as the shape of the yield curve. More specifically, the difference between long-term rates and short-term ones. In normal times, a fixed-income product with a longer time to maturity will have a higher interest rate than one with a shorter time to maturity given the increased risk inherent to the longer holding period. When bondholders perceive that economic conditions are going to deteriorate in the short term which could imply defaults on soon to be repaid debt, however, bonds with longer maturities are purchased, increasing their price and therefore mechanically decreasing their yield. The opposite happens for the shorter end of the yield curve. The perceived risk can go as far as to outweigh the maturity risk completely and invert the yield curve, meaning that the yield on products with a short maturity will be higher than for those with a long maturity, a phenomenon called a yield curve inversion. Although this indicator is based on bond markets, it has been found to have a link to economic activity (Estrella and Hardouvelis, 1991) which impacts the stock market. In our case, we have selected the difference between the ten-year rate and the two-year rate as well as the ten-year and three-month rate with the intention of detecting medium-term and short-term concerns respectively.

One of the United States' Federal Reserve's tools to affect monetary supply and thus, the economy is the Federal Funds rate also known as Monetary Policy 1 or MP1. Although this technically only relates to the overnight inter-bank lending rate, it has a wide-ranging impact on the cost of money at all maturities to a certain extent and " is extremely informative about future movements of real macroeconomic variables, more so than [...] other interest rates" (Bernanke, 1990). As such it also has an effect on ex-post stock returns according to Thorbecke (1997). In addition to this, we also collect the real and nominal ten-year rate with the rationale that they have an effect on the terminal value of companies which is often one of the larges component in discounted-cash-flow models.

3.2 Composite Indicators

As previously mentioned, the origins of market stress are diverse and for this reason, the financial indicators mentioned above might be too simplistic to capture complex stress events.

For this reason, we will benefit from prior research from financial authorities and use composite financial stress indices (FSIs) to gauge market stress. A common denominator of these indicators is that they collect a variety of metrics and indicators, and aggregate them in order to have an idea of the health of various facets of financial markets. Using the findings of Manamperi (2015) we have selected 2 financial stress indices and a third was also chosen due to its daily frequency, wide geographical reach and the availability of the sub-components of the index.

The first FSI we will use is the one provided by the Kansas City Federal Reserve developed in Hakkio and Keeton (2009) and revised in Cook, Doh, et al. (2018) when the LIBOR was discontinued. This index is published on a monthly basis and uses 11 metrics of credit spreads and equity volatility for the U.S.

Next, we explore the Saint-Louis Federal Reserve's FSI developed in Kliesen, Smith, et al. (2010) which differs from the previous index in that it uses 18 indicators related to yields, yield spreads and miscellaneous indicators such as security volatility. It is also updated on a more frequent basis, weekly, allowing for better reactivity of our models.

Although analyzing the geographical distribution of our universe and portfolio has shown to have a clear bias on U.S. Equities, our investment universe is the MSCI World and therefore we have also selected a global FSI. This brings us to the Office of Financial Research's (OFR) FSI developed in Monin (2019). The strengths of this index are its consideration of international markets which is in line with our investment universe, as well as the fact that it provides the sub-elements of the composite index which represent different sources of financial stress, some of which might be more relevant to the flight-to-quality phenomenon, allowing us to try them individually in our strategies and finally, its daily publishing frequency fits our desire to react quickly to stress events. This indicator considers 33 variables from equity and credit markets.

3.3 Transforming the Data

Observing the values of the time series and performing a stationarity test following the methodology of Dickey and Fuller (1979) (c.f. table 33 to table 49 for test results) we notice that out of our 6 standalone metrics and 11 composite indicators, only the VIX results in a rejection of the null hypothesis that it is non-stationary whereas for the 16 others, we do not reject the null hypothesis. This can prove problematic as shown by Granger and Newbold (1974) since it can lead to spurious correlations which could interfere with our models. To remedy this, we perform first-order differencing to the relevant time series and thereafter observe that the null hypotheses of the subsequent Dickey-Fuller tests are all rejected (c.f. table 50 to table 65 for tables)

3.4 Selecting Indicators

Having transformed our indicators into usable features for our models, we will now select the ones which have the best chances of predicting flights to quality. To identify the most suitable indicators, we first identify the relevant indicators and thereafter, eliminate the redundant ones. Although approaches such as those found in Yu and Liu (2004) could prove useful for this type of issue, the small number (17) of features to sift through allows for a more tailored approach.

To find the relevant indicators, we look for those which have values with a statistically significant non-zero slope with the benchmark returns and a statistically significant non-zero slope of the opposite sign with returns of the quality portfolio.

An ideal example of this is the first difference of the OFR FSI as we can see in fig. 3 and fig. 4. table 7 and table 8 show that the slopes of the OLS regression line are significantly different from zero and of opposite signs.

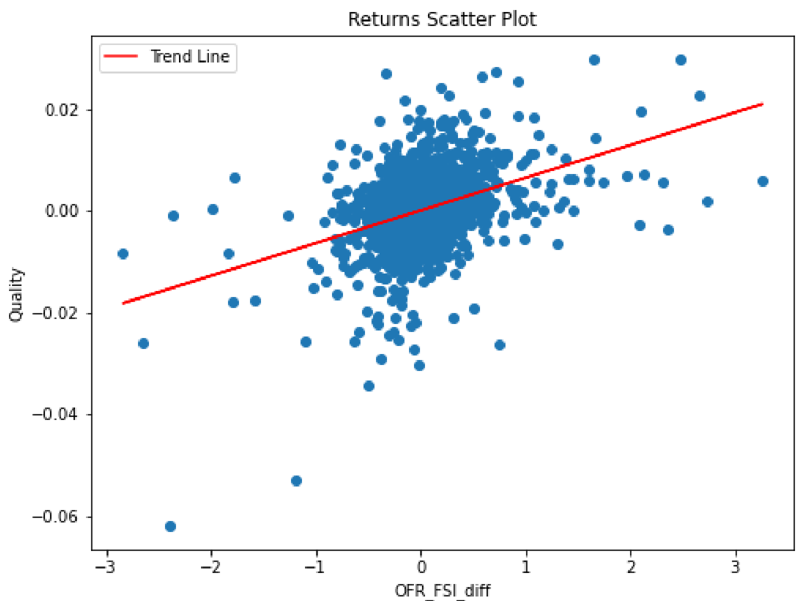

Figure 3

Selecting all the indicators for which the slope criteria are met leads us to omit the ten-year real rate, the Ten year-two year yield spread and the Saint Louis FSI.

Table 7: Coefficients for OFR_FSI_diff on Quality

	Coefficient	Std. Error	T-value	P-value
Intercept	0.000110	0.000080	1.362424	1.731486e-01
OFR_FSI	0.006437	0.000267	24.089184	4.411643e-119

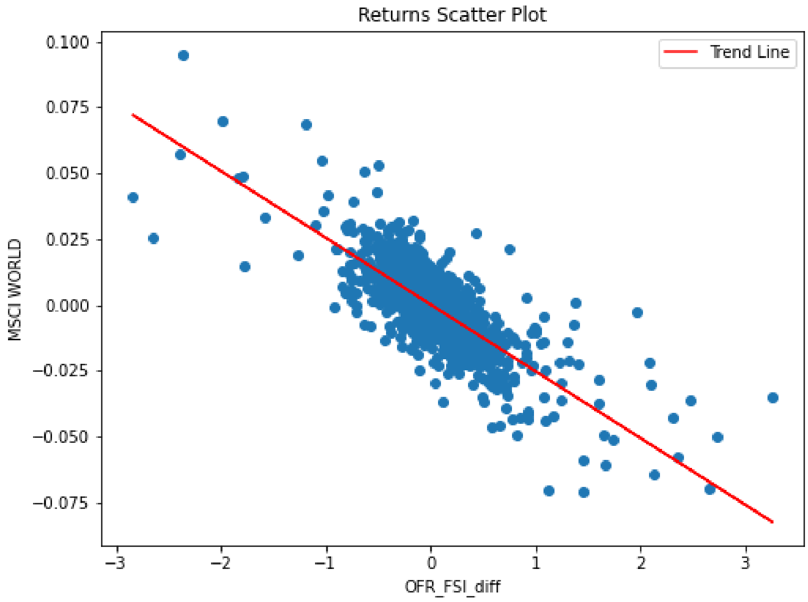

Figure 4

Table 8: Coefficients for OFR_FSI_diff on MSCI WORLD

	Coefficient	Std. Error	T-value	P-value
Intercept	0.000180	0.000111	1.622181	0.104851
OFR_FSI	-0.025331	0.000368	-68.792953	0.000000

This previous selection allowed us to remove the irrelevant indicators but we are still left with 14 which can be used as features in our models. Although the number of observations allows us to be free from the curse of dimensionality, we will still make sure that we are not adding excessive noise by including redundant indicators which would "mislead the learning process" according to Singh et al. (2015). Intuitively, given that we have taken the OFR FSI as well as its sub-components, and knowing that the FSI is simply the sum of its sub-components one can expect the final OFR FSI to be entirely redundant if we have its sub-components. What is more, we have taken both the regional sub-components as well as the category ones which are both just different ways of subdividing the final OFR FSI. Performing a variance inflation factor (VIF) analysis on the 13 relevant indicators does indeed confirm our suspicions.

The large VIFs seen in table 66 indicate a high degree of collinearity for the main OFR FSI as well as its sub-indicators. Removing the OFR FSI and either the regional or category sub-components, we find a much more suitable set of values (see table 69 and table 68) which are well below any thresholds outlined by R. O'Brien (2007). We opt for the removal of the regional sub-components rather than the category ones given that the geographical distribution of our portfolios can fluctuate. This gives us confidence in moving forward with the 9 remaining indicators as features for our models.

4 Flight-to-Quality Investment Strategies

Having constructed a quality factor portfolio which presents a promising opportunity as a hedge during periods of negative market performance and identified indicators which have correlations with the returns of the market and an opposite correlation with the returns of the quality portfolio, we can now attempt to combine the two in order to build flight-to-quality investment strategies going from simplistic models using rule-based portfolio switching, then attempting to apply k-Mean clustering as well as a Hidden Markov Model with the hope that there exists additional information to extract from the indicators which are not self-evident.

We define the guiding principles of our strategies to be to hold the index as much as possible, switch to the quality portfolio during periods of stress and switch back when the dust has settled. These 3 steps stem from the fact that the MSCI World index has a superior risk-adjusted return ratio over the entire period but not when the market declines and stress is high and the number of stocks in the quality portfolio as well as its short component involve considerable trading costs.

4.1 Rule-Based Investing

Our first and most straightforward approach will be to switch to the quality portfolio as soon as at least one of the composite FSIs is above 0 which is, as described previously, the threshold outlined by the entities that publish the FSIs. Back-testing this strategy on the in-sample period and looking at fig. 54 we immediately notice that the amount of days in of stress outnumbers the amount of normal days. This leads the strategy to follow the quality portfolio quite closely, and only switching to the market portfolio less than 20% of the time. As a result, table 71 shows that the risk-adjusted return of outperforms the standard quality portfolio but not the benchmark.

Nevertheless, table 70 demonstrates an, albeit minor, ability to discern a regime where volatility is higher overall and the difference between risk-adjusted performance measures is diminished. The market remains the best bet however according to the ratios computed here.

During the in-sample period however, the ratio of normal days to stress days is twice as high as for the in-sample as seen in fig. 55. As a consequence, the overall performance seen in table 73 is much better and almost beats the benchmark. Furthermore, the regimes identified by this rudimentary technique this time show that the quality portfolio becomes an interesting alternative to the market during periods of stress by not only becoming more defensive but also offering an attractive performance that outpaces the risk-adjusted return of the benchmark.

Although this simple approach is already promising, we would like to see if there are less obvious patterns in the data which could be identified by unsupervised models.

4.2 k-Means

Even though the composite indicators have been constructed in order for above zero values to represent periods of stress, the other variables we want to include have no explicit relation to these periods. Hence we would like to be able to infer regime changes from the data without having to set predetermined thresholds. To this end, we will apply an unsupervised machine-learning algorithm to our data to find clusters of periods with significant differences.

To be more specific, we use the k-Means method formalised in Lloyd (1982) which groups data points so as to minimize the variance within each cluster. Formally, the objective function seen in section I.1 is optimized in 3 steps.

Firstly, the clusters are initialized. In the most basic k-Means model, this means that k data points are chosen at random to be the centroids of the clusters. This method can however lead to sub-optimal results if the centroids are too close together for example. This is why we opt for the k-Means++ initialization algorithm which starts by selecting the first centroid at random amongst the data points. Then, the distance of all remaining data points to the closest centroid (at first there is only one) is computed. Next, the second centroid is chosen randomly with the square of the previously calculated distance used to weigh the selection probability. The distance computation and centroid selection steps are reiterated until k centroids have been obtained. Having selected the initial positions for our centroids, we assign each point to the nearest centroid so as to form k clusters. Thereafter, we update the centroids to be the mean of each point within a given cluster. The assignment and update steps are iterated until convergence or a stopping criterion is met.

Given our investment objectives, we set the number of clusters to 2 and find satisfactory results in table 74 for the in-sample period with one cluster being characterized by outperformance of quality and the other where the market portfolio prevails. As a consequence, switching portfolios in line with this fact results in a marked increase in risk-adjusted returns relative to the two portfolios as we can see in fig. 56 and table 75.

Furthermore, fitting this model on the out-sample data, the outcome appears to remain robust. Indeed, table 76 shows that the relative performance of the quality portfolio versus the market remains better during periods of stress and worse in the calmer periods and the performance achieved with a portfolio switching is significantly improved as shown in fig. 57 and table 77.

Although the outcome has proven satisfactory, there are limitations to this model. First and foremost, it takes all the points on an individual basis and does not take the temporal order of our observations into account which can be critical in time series data. Nevertheless, even though Chen et al. (2021) explore alternative clustering methods for time series data such as k-Shape, the simplicity of k-Means was shown to outweigh its setbacks.

4.3 Hidden Markov-Model

Taking a different approach to identifying separate regimes in our time series which accounts for the chronological ordering, we apply the commonly used Hidden Markov Model (HMM). First described in Baum and Petrie (1966), HMMs are based upon the principle that there exists a Markov process of unobservable states with observable outcomes which are influenced by the states called emissions. Given that our data is not necessarily

Gaussian, we verify if there exists a number of mixture components above 1 which would warrant using a Gaussian Mixture version to train our HMM. Computing the Bayesian Information Criterion (BIC) defined in Schwarz (1978) to determine the number of Gaussian components which best describes our data (see table 78) concludes that 1 suffices meaning that we can use the standard Gaussian HMM. More formally, this means there exists:

- A set of hidden states $S = \{S_1, S_2, \dots, S_N\}$,
- A transition matrix $A = \{a_{ij}\}, \quad \text{where} \quad a_{ij} = P(S_j \mid S_i)$ represents the probability of switching from state S_i to states S_j,
- A set of vectors of observations (our stress indicators) $O = \{O_1, O_2, \dots, O_T\}$,
- A set of mean vectors $\mu = \{\mu_1, \mu_2, \dots, \mu_N\}$ and covariance matrices $\Sigma = \{\Sigma_1, \Sigma_2, \dots, \Sigma_N\}$ which describe the normal probability density functions governing the emission probabilities as $P(O_t \mid q_t = S_i) = \mathcal{N}(O_t; \mu_i, \Sigma_i)$.
- a vector of initial state probabilities $\pi = \{\pi_1, \pi_2, \dots, \pi_N\}$

Fitting such a model on our data requires to optimize the objective function found in section I.2. To do this, a variant of the Expectation-Maximization algorithm called the Baum-Welch algorithm is applied which involves 3 main steps. First, the model parameters in Θ are initialized, in our case, at random. Then, in the so-called Expectation step, we compute the expected values of the hidden states at each time step given the observed data and the current model parameters using a forward-backward algorithm. In the forward pass, the forward probability $\alpha_i(t)$ of being in hidden state S_i at time t with the path of observations $O_1, O_2, \dots, O_t$ is computed recursively with:

$$\alpha_i(1) = \pi_i P(O_1 \mid q_1 = S_i) \tag{6}$$

$$\alpha_i(t+1) = P(O_{t+1} \mid q_{t+1} = S_i) \sum_{j=1}^{N} \alpha_j(t) a_{ij} \tag{7}$$

The backward pass aims to determine the probability $\beta_i(t)$ of the sequence of observations to end in $O_{t+1}, O_{t+2}, \dots O_T$ given an initial state S_i at time t. This is again solved recursively with:

$$\beta_i(T) = 1 \tag{8}$$

$$\beta_i(t) = \sum_{j=1}^{N} \beta_j(t+1) a_{ij} P(O_{t+1} \mid q_{t+1} = S_j) \tag{9}$$

Having completed the forward and backward passes allows us to move to the maximisation step which aims to update the parameters in Θ based on the posterior probabilities resulting from the Expectation step. To do this, we define two intermediary variables:

$$\gamma_i(t) = P(q_t = S_i \mid O, \theta) = \frac{P(q_t = S_i, O \mid \theta)}{P(O \mid \theta)} = \frac{\alpha_i(t)\beta_i(t)}{\sum_{j=1}^{N} \alpha_j(t)\beta_j(t)} \tag{10}$$

the probability of being in state S_i at time t given the whole sequence of observations,

$$\begin{aligned} \xi_{ij}(t) = P(q_t = S_i, q_{t+1} = j \mid O, \theta) &= \frac{P(q_t = i, q_{t+1} = j, O \mid \theta)}{P(O \mid \theta)} \\ &= \frac{\alpha_i(t) a_{ij} \beta_j(t+1) P(O_{t+1} \mid q_{t+1} = S_j)}{\sum_{k=1}^{N} \sum_{w=1}^{N} \alpha_k(t) a_{kw} \beta_w(t+1) P(O_{t+1} \mid q_{t+1} = S_w)} \end{aligned} \tag{11}$$

We then update Θ as follows:

$$\pi_i = \gamma_i(1) \tag{12}$$

$$a_{ij} = \frac{\sum_{t=1}^{T-1} \xi_{ij}(t)}{\sum_{t=1}^{T-1} \gamma_i(t)} \tag{13}$$

$$P(o \mid q_t = S_i) = \frac{\sum_{t=1}^{T} \delta(O_t = o)\gamma_i(t)}{\sum_{t=1}^{T} \gamma_i(t)} \tag{14}$$

Where

$\delta(O_t = o) = 1$ if $O_t = o$ and 0 otherwise

The expectation and maximisation steps are then repeated until convergence or a fixed number of iterations has been reached.

Once Θ has been estimated (i.e. the model has been fitted to the training data), we can now determine the most likely sequence of states given the observations. To do this, the Viterbi algorithm (Viterbi, 1967) which occurs in 5 steps. First two NxT matrices, the path probability matrix ,δ as well as the backpointer matrix, ψ are created. In the former, each element $\delta_{it} = P(q_t = S_i, \mid O_{1:t}\Theta)$ represents the most probable path that ends in S_i

at time t, given the observed sequence up to time t and the model parameters. In the latter, each element ϕ_{it} stores most probable the path which leads to S_i at time t. these matrices are initialized with:

$$\delta_{i,1} = \pi_i P(O_1 \mid q_1 = S_i) \tag{15}$$

and

$$\psi_{i,1} = 0 \quad \text{(A dummy value)} \tag{16}$$

Next is a recursive step where for each time step $t = 2$ to T, and each state $j = 1$ to N we compute:

$$\delta_{j,t} = \max_{i=1}^{N} \left(\delta_{i,t-1} \cdot a_{i,j}\right) P(O_t \mid q_t = S_j) \tag{17}$$

$$\psi_{j,t} = \arg\max_{i=1}^{N} \left(\delta_{i,t-1} a_{i,j}\right) \tag{18}$$

Thereafter, the third step is to find the maximum probability over all final states at time T.

$$P^* = \max_{j=1}^{N} \delta_{j,T} \tag{19}$$

Finally, we backtrace the states from $t = T - 1$ to 1 using the backpointer matrix to determine the most likely sequence of states q^* with:

$$q_t^* = \psi_{q_{t+1}^*, t+1}. \tag{20}$$

Setting the number of states to 2 and fitting this model on our in-sample data yields positive results. Indeed, table 79 shows that one state is characterised by an increase in risk for both portfolios and by an outperformance of the quality factor whereas in the other state, the market portfolio is the better option. This model differs sizeably from the k-Means model during the in-sample period however as there are close to twice as many periods of heightened stress risk characteristics which makes the resulting strategy resemble the quality portfolio much more closely as we can see in fig. 58 and table 80.

During the out-sample periods, in contrast, the HMM specification identifies almost the same number of periods of stress with 242 versus 228 for the k-Means. Despite the similar number of periods, the behaviour of the quality factor is worse than the periods determined by clustering as shown by the moderate risk-adjusted return values in table 81. Nevertheless, the relative outperformance of quality in the stressed periods and underperformance in normal periods remains which makes building a switching strategy interesting. The end result of the strategy remains quite similar, however.

5 Conclusions

In conclusion, by following the guiding principles of Asness et al. (2019) quality factor methodology and leveraging Hsu et al. (2019) findings to refine the variable selection process, we have successfully constructed a quality factor portfolio that exhibits a negative correlation with the market, particularly during challenging market conditions. This defensive portfolio offers a risk-mitigating opportunity for investors.

Our focus then shifted to identifying indicators that could signal periods of market turbulence. Through comprehensive analysis, including commonly used indicators by market practitioners and composite indicators published by financial authorities, we identified indicators with a significant correlation to market returns and an inverse relationship with the quality factor portfolio, most notable of which was the Office for Financial Research's Financial Stress Index developed in Monin (2019).

Furthermore, by implementing a rule-based strategy using composite financial stress indicators, we achieved superior risk-adjusted returns in our test sample. Employing k-Means clustering and Hidden Markov Model techniques, we uncovered two distinct regimes characterized by varying risk profiles where the defensive quality portfolio is better suited for navigating one regime, while the other regime presents an environment where market risks are adequately rewarded.

The findings of our research have practical implications for investors and financial practitioners, offering valuable insights for risk management and portfolio optimization. However, it is important to acknowledge the limitations of our study, including the specific dataset used and the assumption of stationary market dynamics. Further research could explore additional indicators such as macroeconomic ones and refine the regime detection methodologies to enhance the applicability and robustness of our findings.

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Appendix

I Model Formalizations

I.1 k-Means

The k-Means objective function is:

$$\underset{S}{\operatorname{argmin}} \sum_{i=1}^{k} \sum_{x \in S_i} ||x - \mu_i||^2 \tag{21}$$

Where μ_i is the mean of points within S_i computed as

$$\mu_i = \frac{1}{|S_i|} \sum_{x \in S_i} x \tag{22}$$

k = is the number of clusters

S_i = The set of points within cluster i

$|S_i|$ = The number of points within S_i

Which equates to:

$$\underset{S}{\operatorname{argmin}} \sum_{i=1}^{k} |S_i| Var(S_i) \tag{23}$$

I.2 HMM

The HMM parameter estimation objective function is:

$$\underset{\Theta}{\operatorname{argmax}} P(O|\Theta) = \sum_{\text{all state sequences}} \left(\prod_{t=1}^{T} P(O_t|q_t, \mu, \Sigma) P(q_t|q_{t-1}, A) \right) \tag{24}$$

Where

$$
\begin{aligned}
O &= \{O_1, O_2, \ldots, O_T\}, \text{ the sequence of observations} \\
\Theta &= \{\pi, A, \mu, \Sigma\} \\
N &= \text{The number of hidden states} \\
\pi &= \{\pi_1, \pi_2, \ldots, \pi_N\}, \text{ the initial state probabilities} \\
\textstyle\sum_{i=1}^{N} \pi_i &= 1 \\
A &= \{a_{ij}\}, \text{ the transition matrix} \\
a_{ij} &= P(q_t = j | q_{t-1} = i) \\
\textstyle\sum_{j=1}^{N} a_{ij} &= 1 \\
\mu &= \{\mu_1, \mu_2, \ldots, \mu_N\}, \text{ the state mean vectors} \\
\Sigma &= \{\Sigma_1, \Sigma_2, \ldots, \Sigma_N\}, \text{ the state covariance matrices} \\
q_t &= \text{the state at time t}
\end{aligned}
$$

II Plots

II.1 Defining Quality Plots

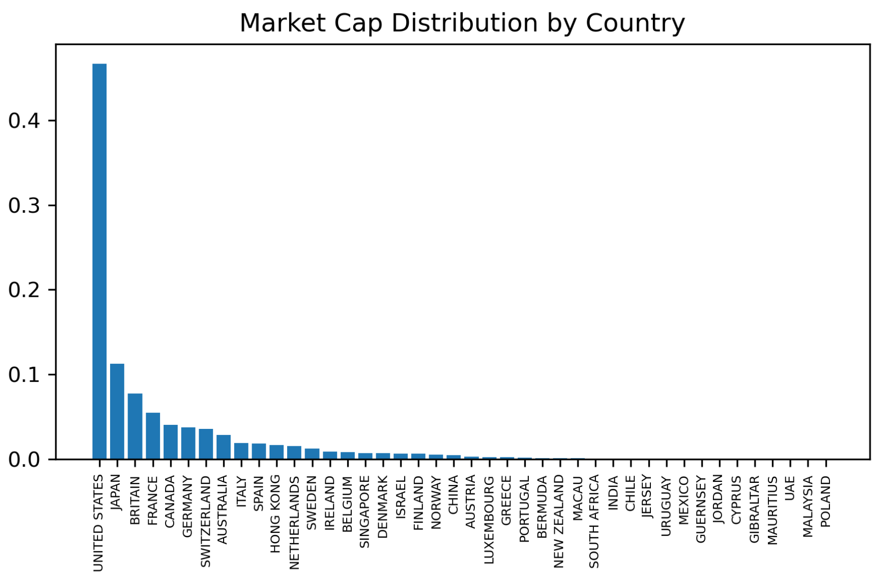


Figure 5

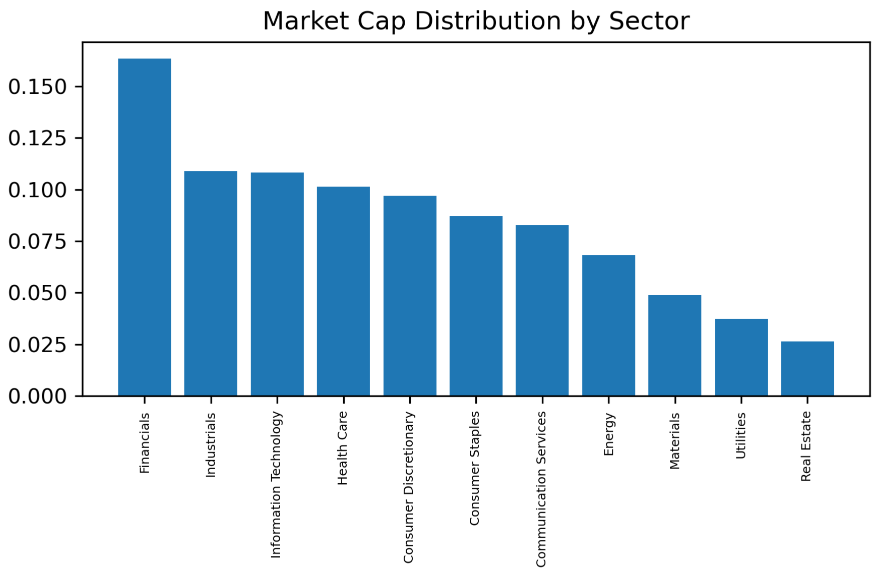


Figure 6

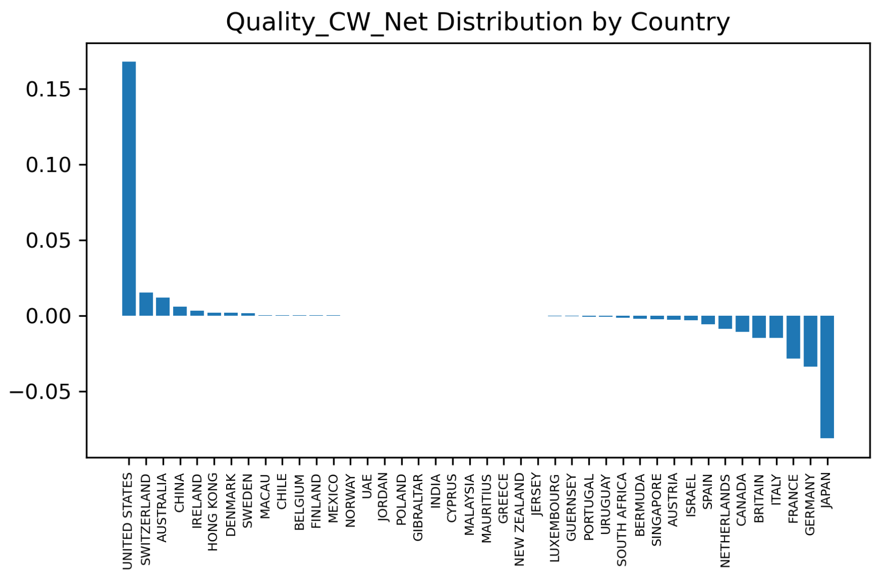


Figure 7

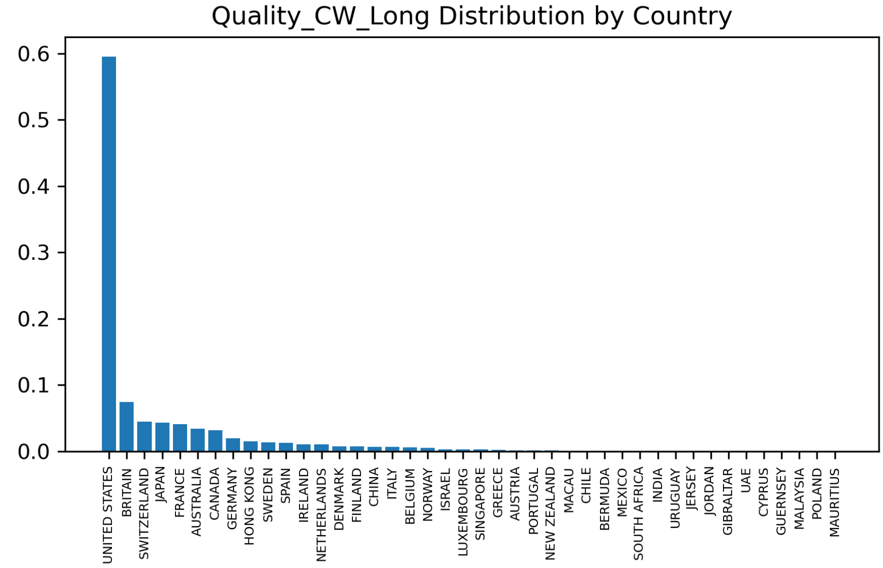


Figure 8

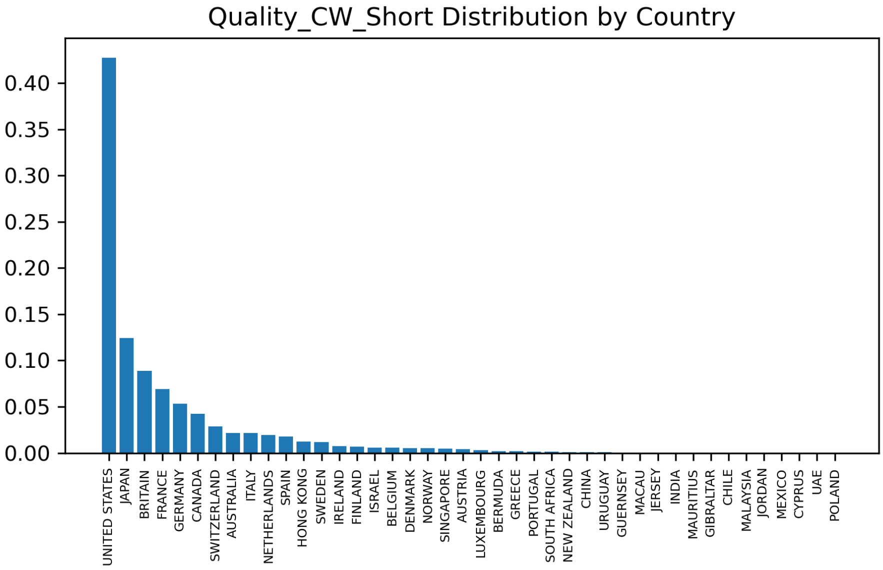


Figure 9

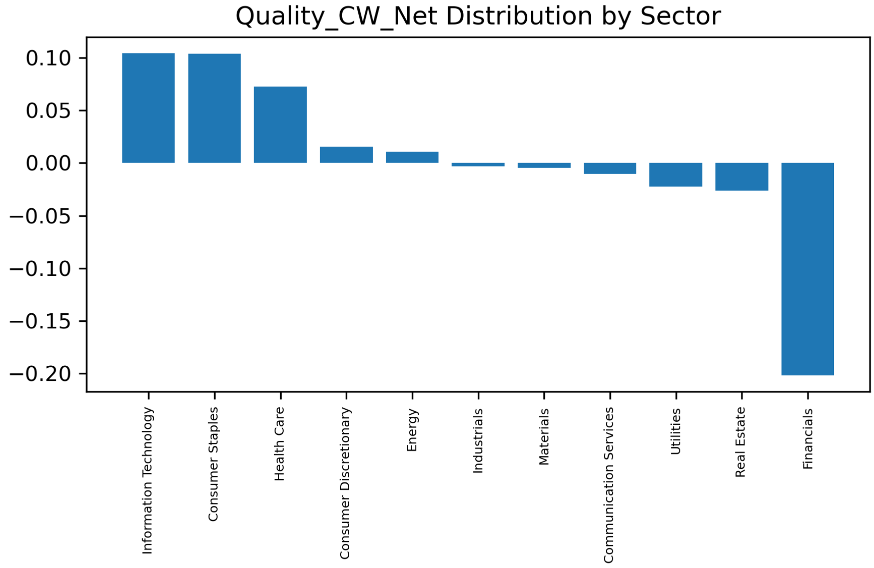


Figure 10

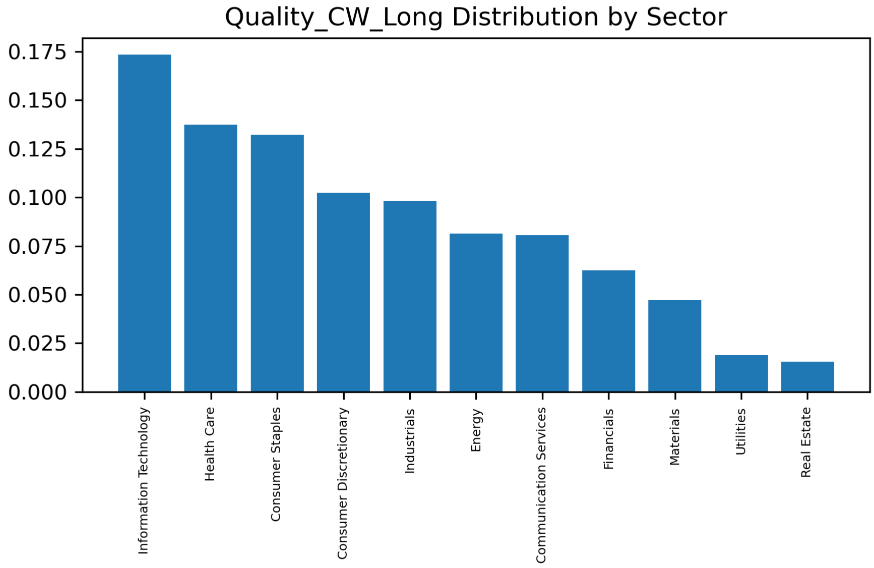
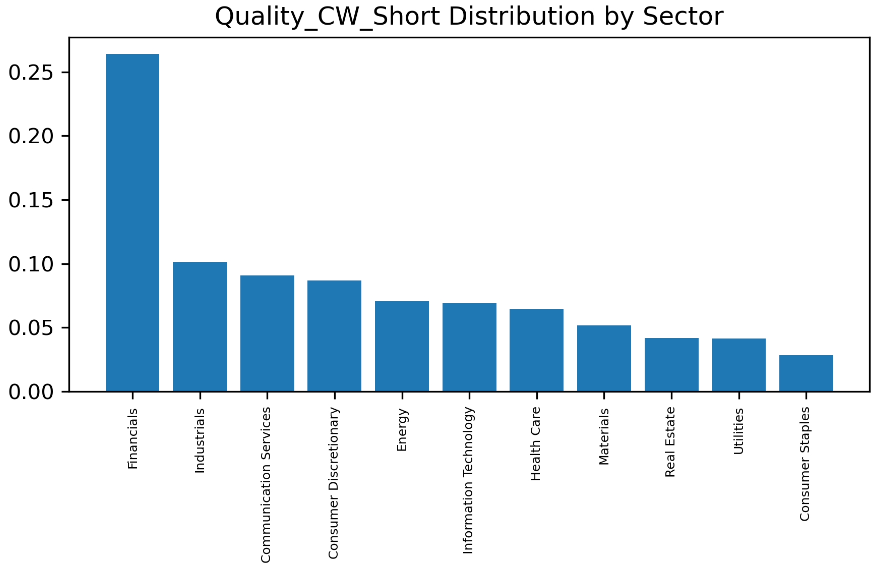


Figure 11



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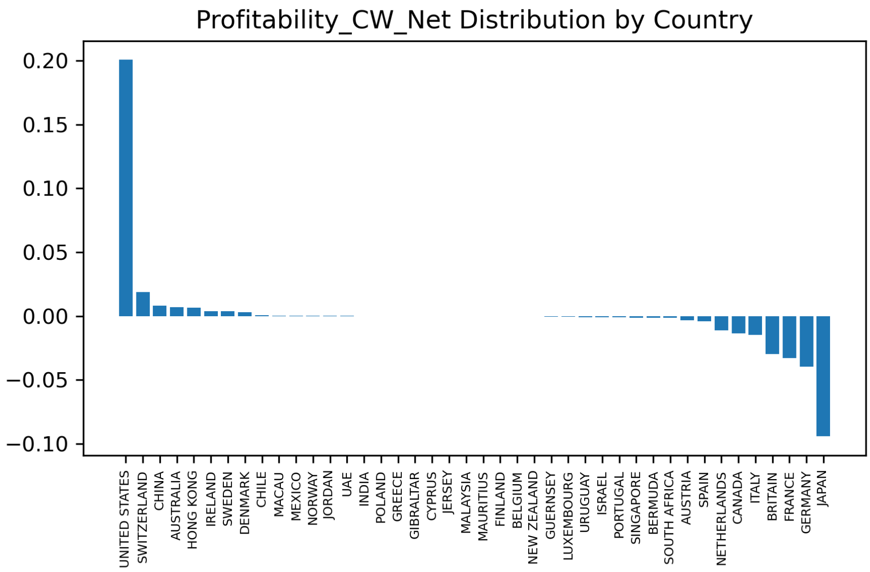

Figure 13

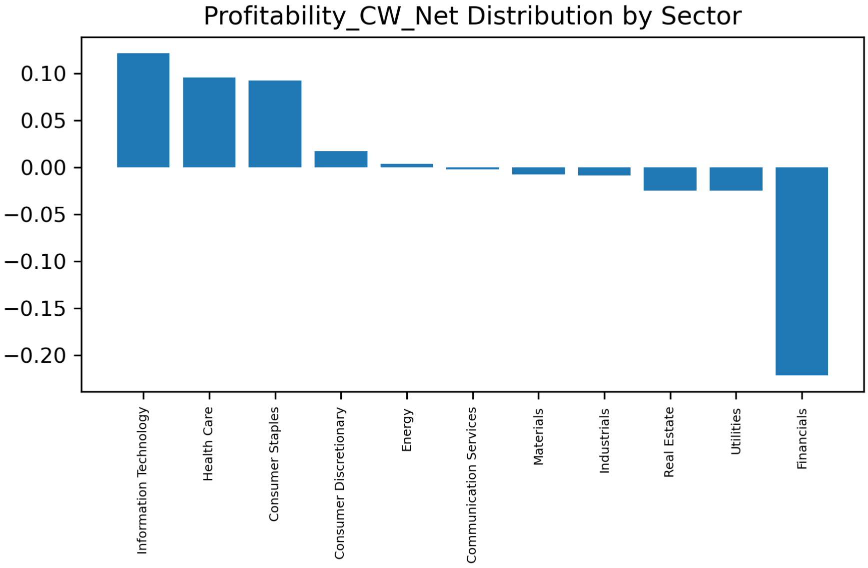

Figure 14

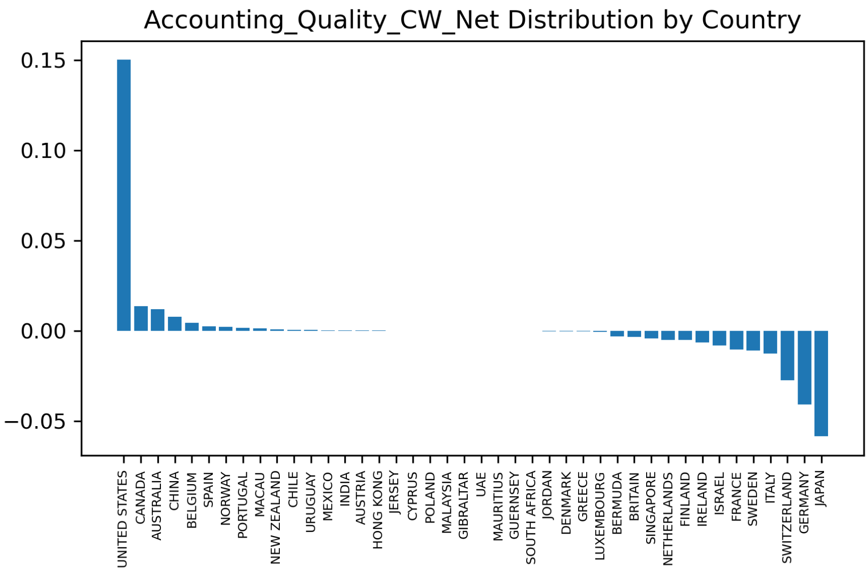

Figure 15

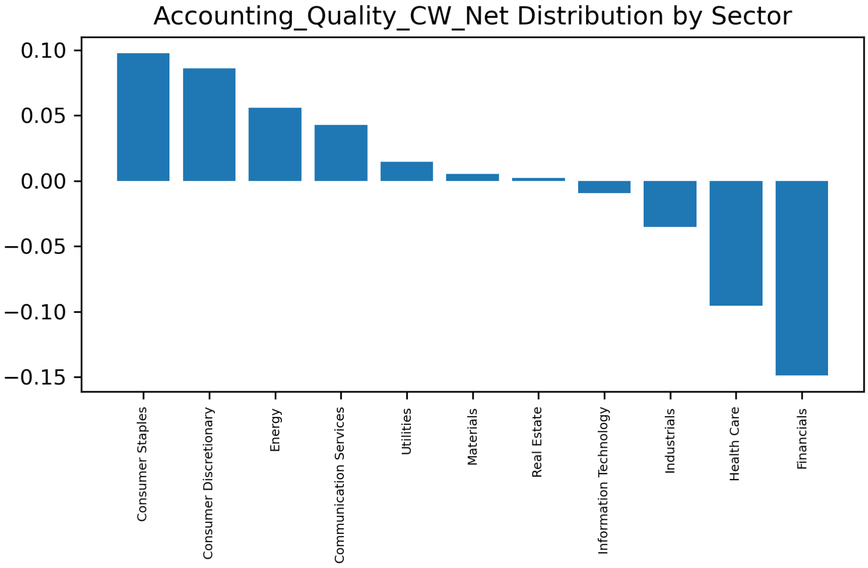

Figure 16

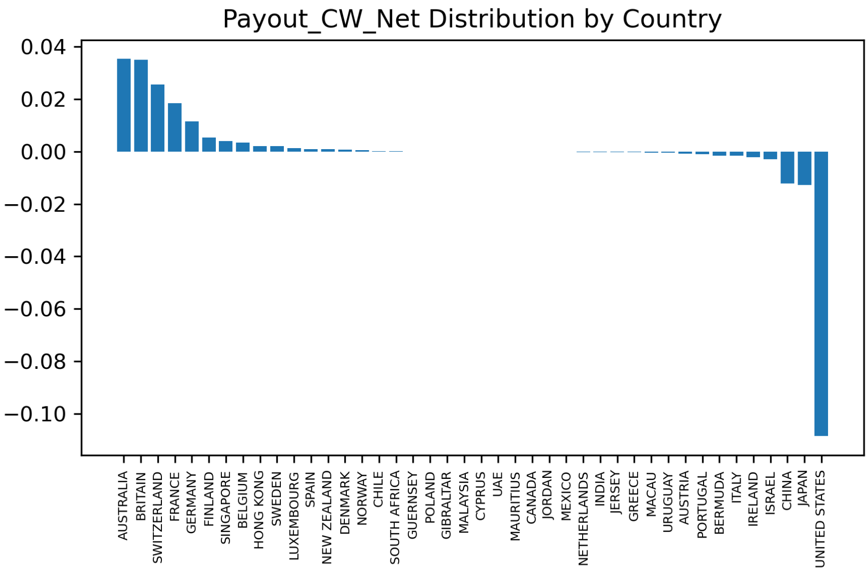

Figure 17

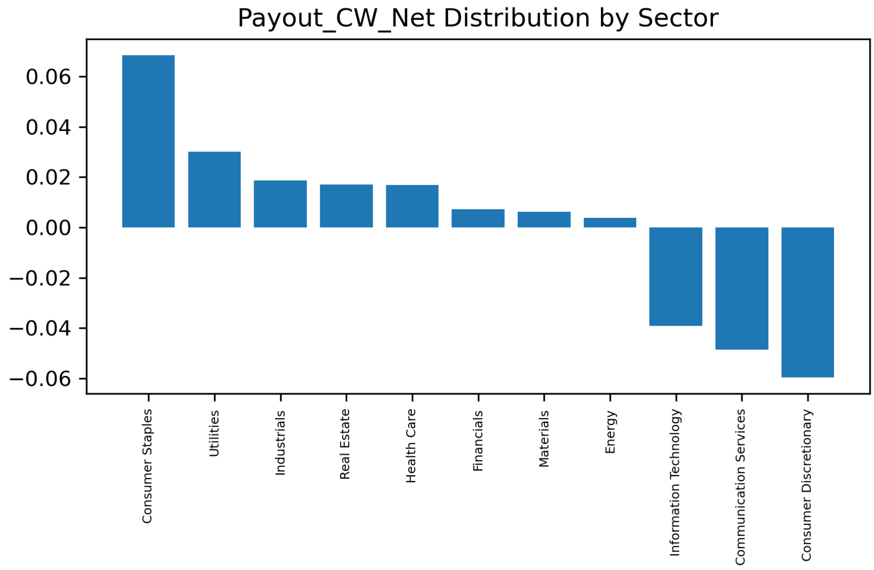

Figure 18

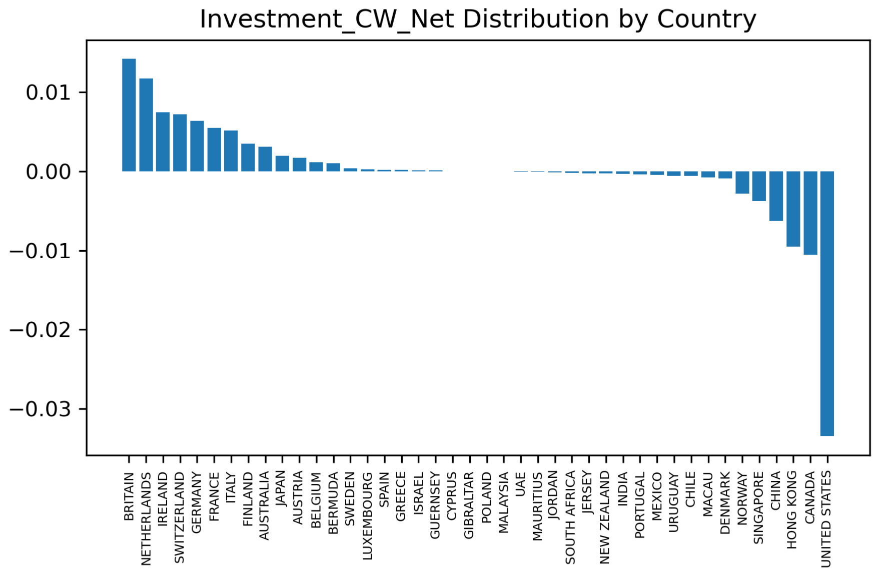

Figure 19

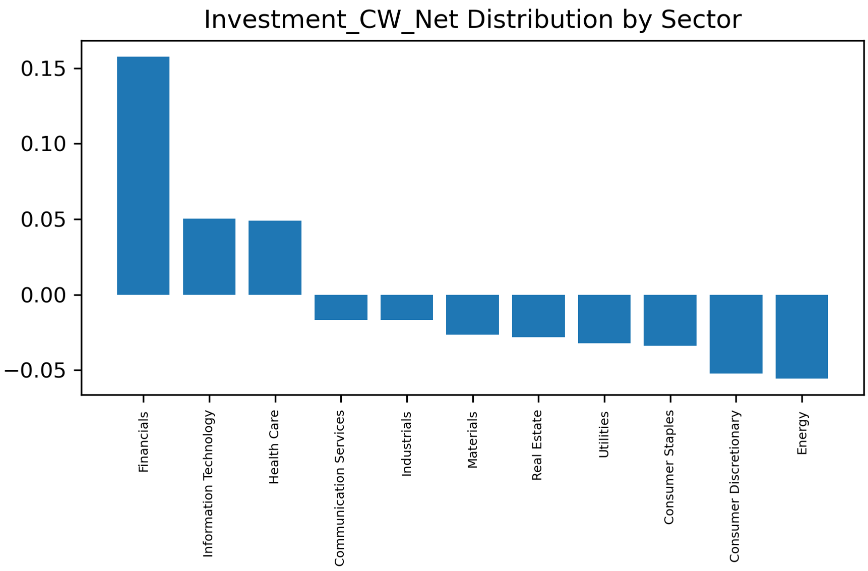
Investment_CW_Net Distribution by Sector
0.15
0.10
0.05
0.00
−0.05
Financials
Information Technology
Health Care
Communication Services
Industrials
Materials
Real Estate
Utilities
Consumer Staples
Consumer Discretionary
Energy

Figure 20

II.2 Detecting Financial Stress Plots

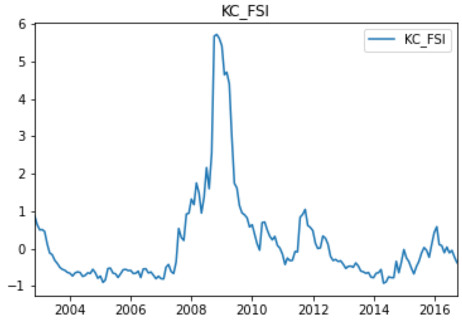

Figure 21: Kansas City Fed FSI

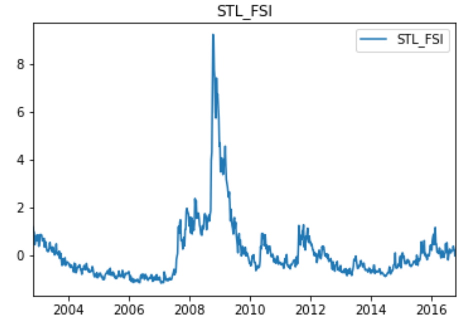

Figure 22: Saint Louis Fed FSI

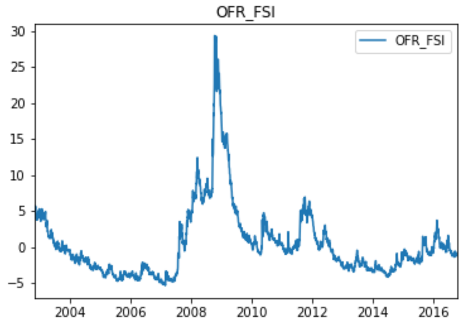

Figure 23: OFR FSI

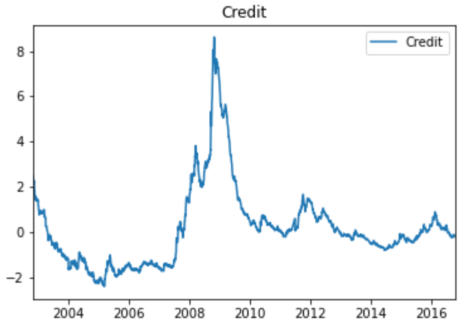

Figure 24: Credit OFR FSI

Figure 25: Emerging Markets OFR FSI

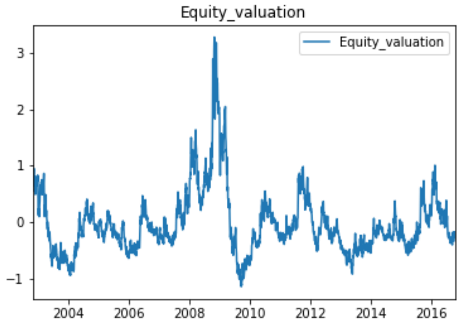

Figure 26: Equity Valuation OFR FSI

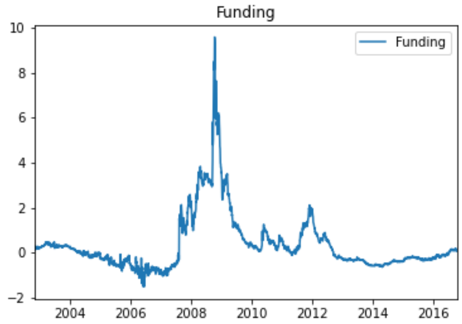

Figure 27: Funding OFR FSI

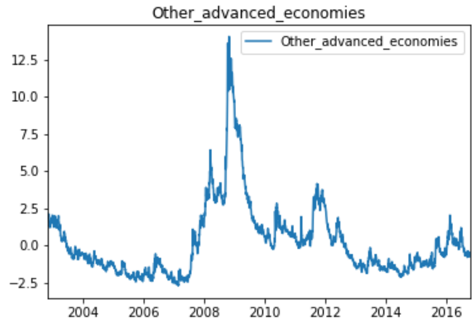

Figure 28: Other Advanced Economies OFR FSI

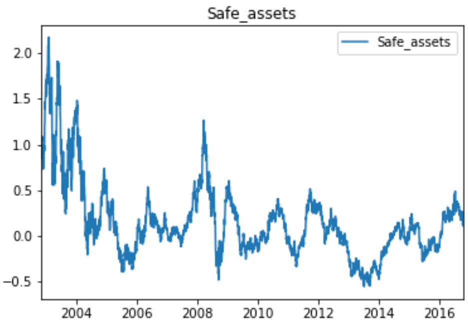

Figure 29: Safe Assets OFR FSI

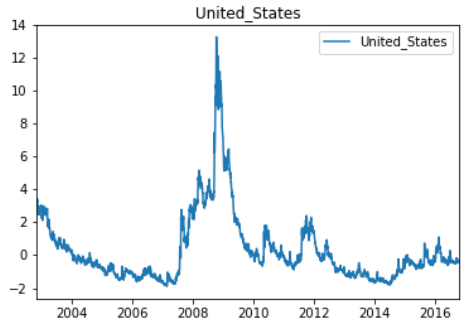

Figure 30: United States OFR FSI

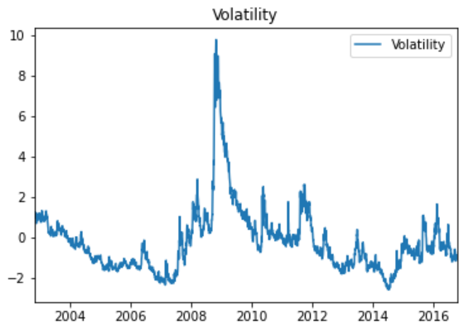

Figure 31: Volatility OFR FSI

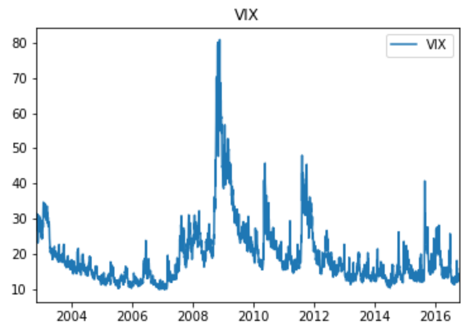

Figure 32: VIX

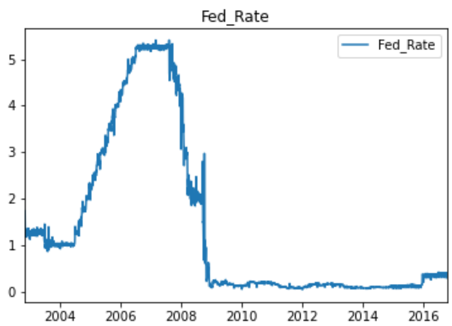

Figure 33: Federal Funds Rate

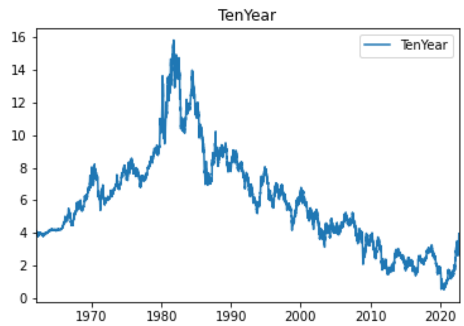

Figure 34: Ten Year Yield

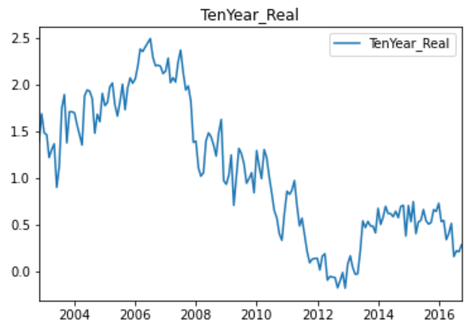

Figure 35: Ten Year Real Yield

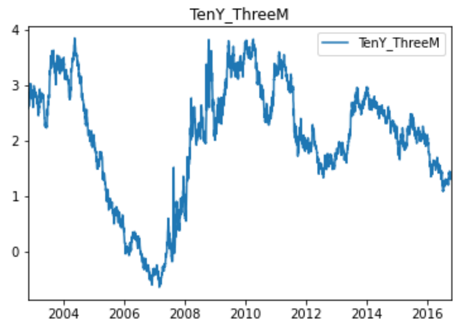

Figure 36: Ten Year - Three Month Yield Spread

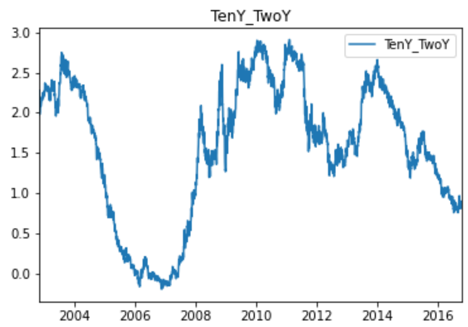

Figure 37: Ten Year - Two Year Yield Spread

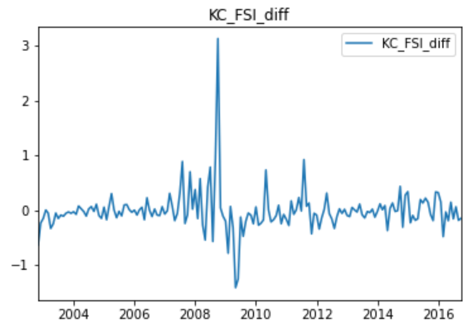

Figure 38: Kansas City Fed FSI (difference)

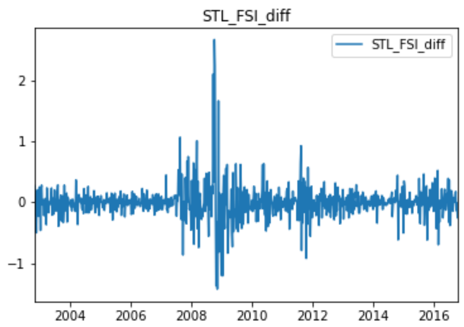

Figure 39: Saint Louis Fed FSI (difference)

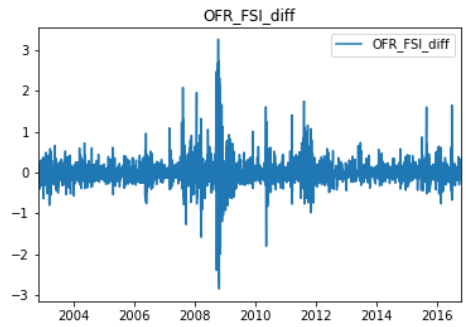

Figure 40: OFR FSI (difference)

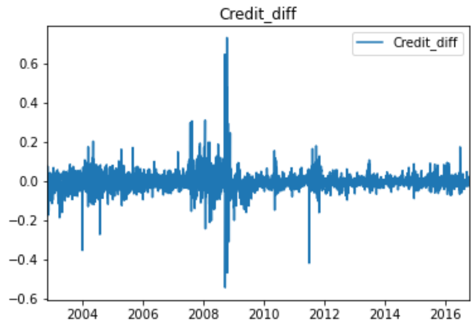

Figure 41: Credit OFR FSI (difference)

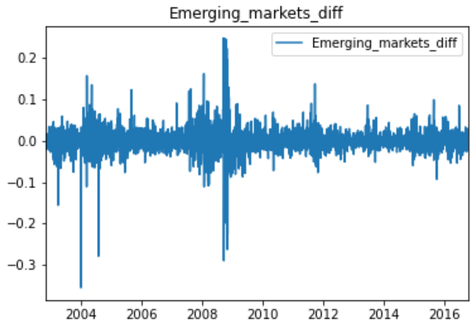

Figure 42: Emerging Markets OFR FSI (difference)

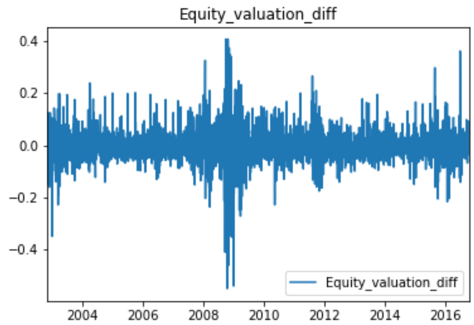

Figure 43: Equity Valuation OFR FSI (difference)

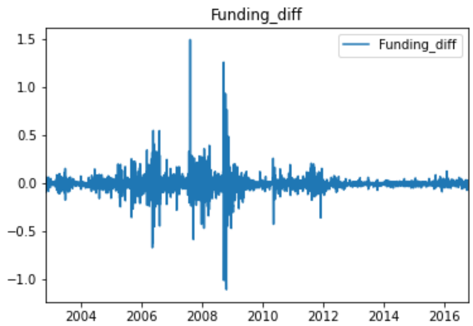

Figure 44: Funding OFR FSI (difference)

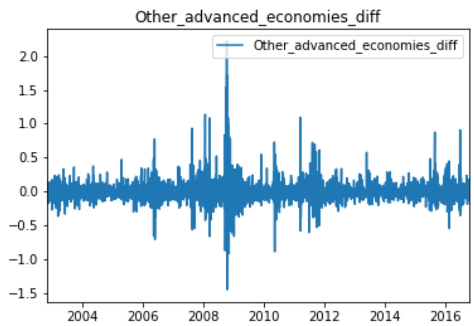

Figure 45: Other Advanced Economies OFR FSI (difference)

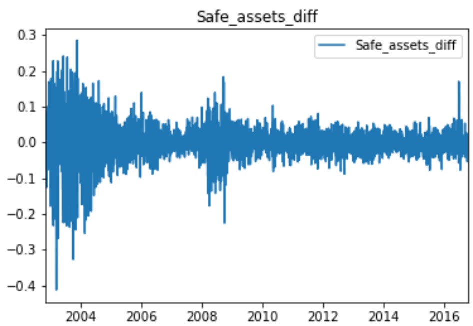

Figure 46: Safe Assets OFR FSI (difference)

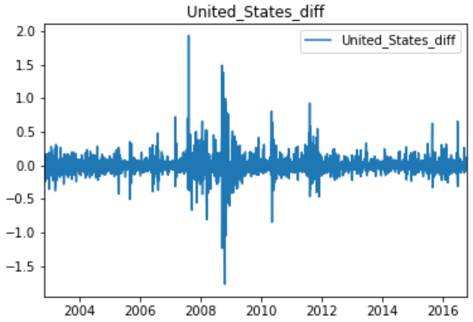

Figure 47: United States OFR FSI (difference)

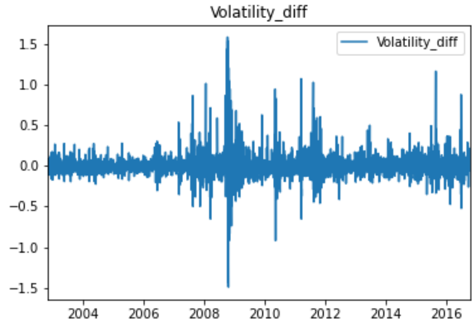

Figure 48: Volatility OFR FSI (difference)

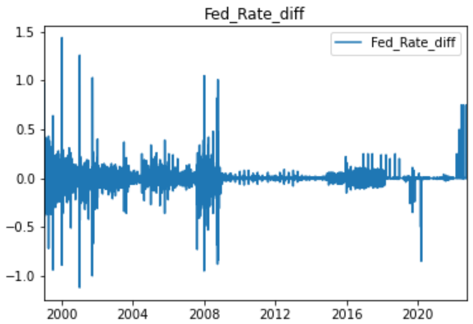

Figure 49: Federal Funds Rate (difference)

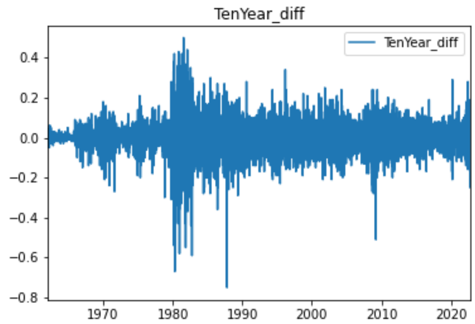

Figure 50: Ten Year Yield (difference)

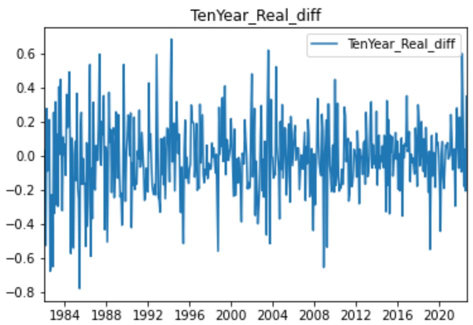

Figure 51: Ten Year Real Yield (difference)

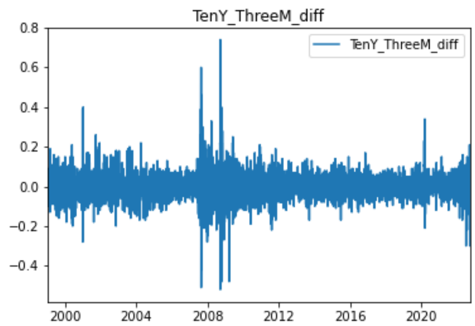

Figure 52: Ten Year - Three Month Yield Spread (difference)

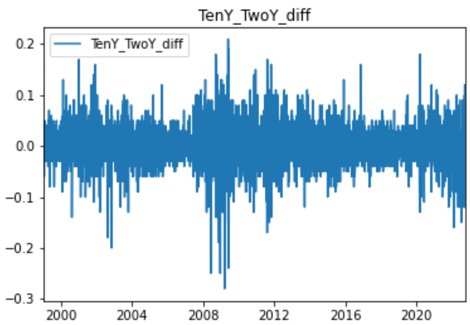

Figure 53: Ten Year - Two Year Yield Spread (difference)

II.3 Investment Strategies Plots

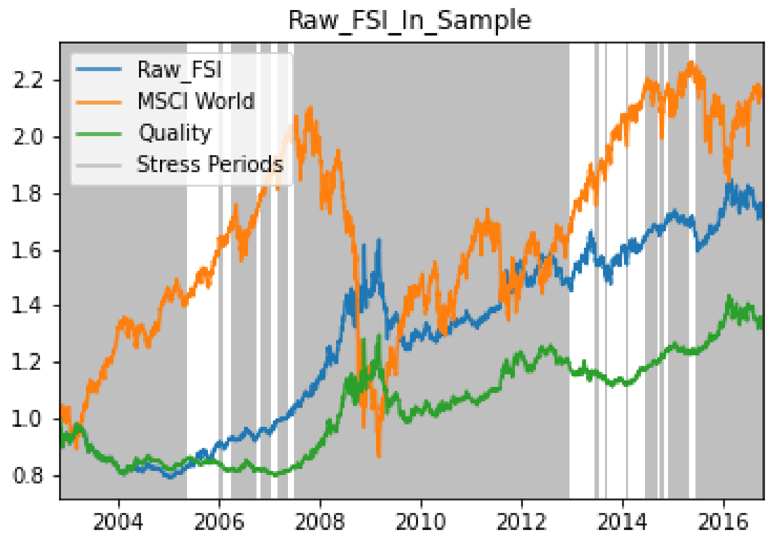

Figure 54

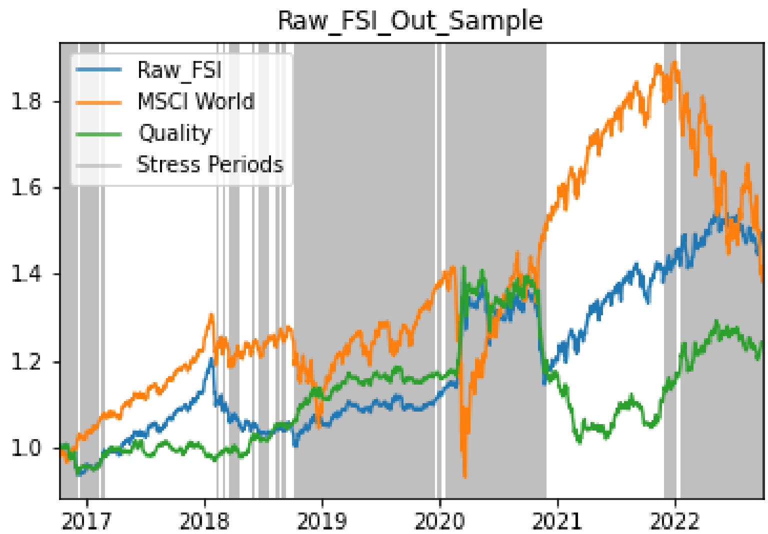

Figure 55

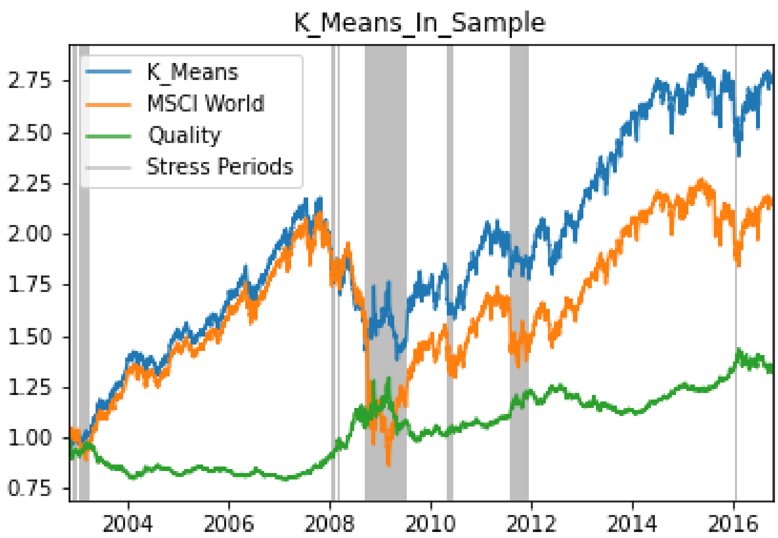

Figure 56

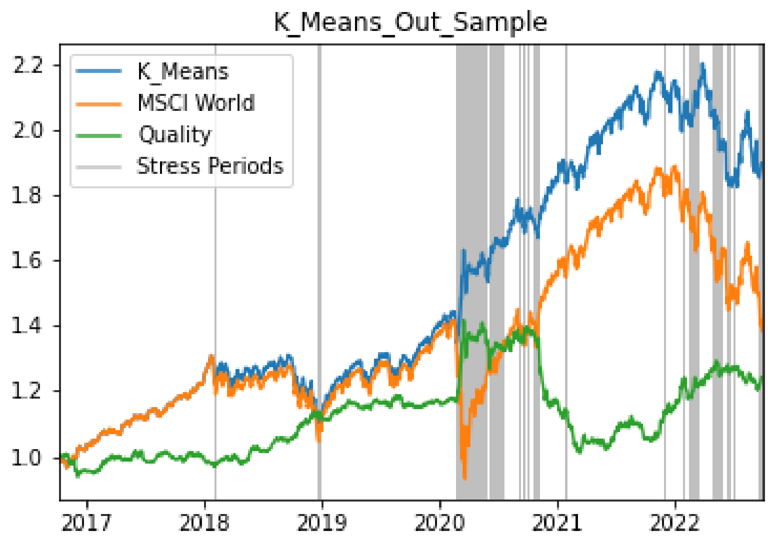

Figure 57

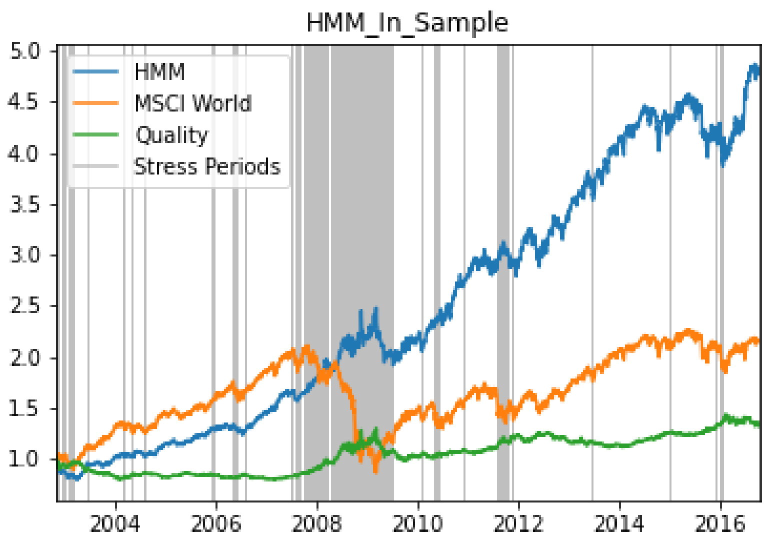

Figure 58

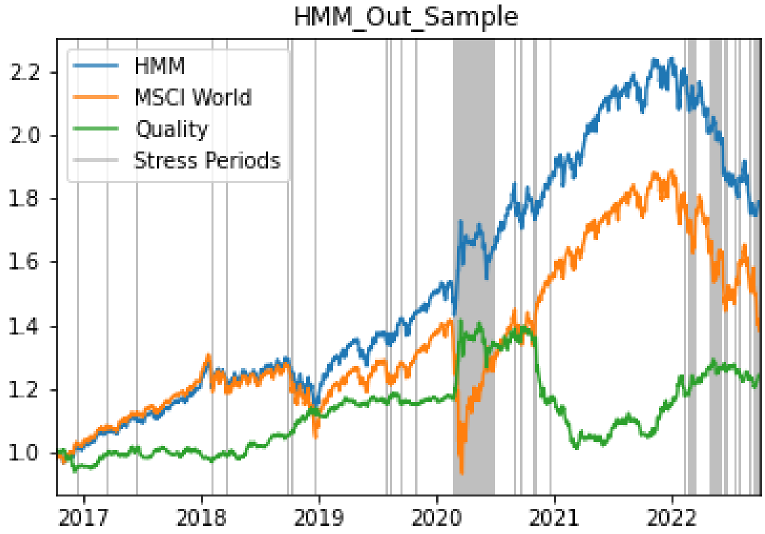

Figure 59

III Tables

III.1 Defining Quality Tables

	ROE
count	594887.000000
mean	11.562290
std	966.609401
min	-63040.820000
25%	4.540000
30%	6.020000
50%	11.030000
70%	16.910000
75%	18.880000
max	369133.330000

Table 9: ROE Statistics

	ROA
count	612332.000000
mean	4.143251
std	25.162529
min	-1385.000000
25%	0.998025
30%	1.561814
50%	3.986974
70%	6.878052
75%	7.929349
max	6408.532466

Table 10: ROA Statistics

	COGS_to_Sales
count	150752.000000
mean	63.192961
std	323.692447
min	-532.685905
25%	44.723797
30%	49.292377
50%	63.803851
70%	74.690539
75%	77.249150
max	83494.114550

Table 11: COGS to Sales Statistics

	PM
count	2.185090e+05
mean	1.086008e+02
std	5.088527e+04
min	-2.506957e+04
25%	2.271007e-02
30%	3.228915e-02
50%	7.115385e-02
70%	1.278285e-01
75%	1.492564e-01
max	2.378602e+07

Table 12: Profit Margin Statistics

	SoR
count	1.684980e+05
mean	-3.971483e-18
std	9.997566e-01
min	-1.730876e+00
25%	-8.658210e-01
30%	-6.924979e-01
50%	0.000000e+00
70%	6.926403e-01
75%	8.658213e-01
max	1.730884e+00

Table 13: Sales on Receivables Statistics

	CFO_to_NI
count	217726.000000
mean	1.577430
std	275.250752
min	-91247.000001
25%	0.338675
30%	0.619494
50%	1.358491
70%	2.160174
75%	2.478161
max	38597.000007

Table 14: CFO to Net Income Statistics

	Payout_Ratio
count	1.783340e+05
mean	8.074736e+12
std	3.409930e+15
min	-2.156247e+01
25%	7.429620e+00
30%	1.335554e+01
50%	2.972414e+01
70%	5.053182e+01
75%	5.847402e+01
max	1.440000e+18

Table 15: Payout Ratio Statistics

	DIss
count	1.988860e+05
mean	inf
std	NaN
min	-3.342148e+00
25%	-4.964245e-02
30%	-3.371533e-02
50%	-1.157052e-04
70%	3.595028e-02
75%	5.686553e-02
max	inf

Table 16: Debt Issuance Statistics

	EIss
count	2.046040e+05
mean	inf
std	NaN
min	-2.914485e+04
25%	-2.955066e-02
30%	-1.972009e-02
50%	9.444726e-03
70%	3.961279e-02
75%	5.019429e-02
max	inf

Table 17: Equity Issuance Statistics

	Capex_to_DnA
count	212289.000000
mean	18.784536
std	2670.221020
min	-1472.499897
25%	0.522129
30%	0.604717
50%	0.929866
70%	1.367146
75%	1.535628
max	916421.020967

Table 18: CapEx to DnA Statistics

	Asset_Growth
count	2.120660e+05
mean	inf
std	NaN
min	-1.000000e+00
25%	-2.248956e-02
30%	-1.536067e-02
50%	6.681061e-03
70%	3.131441e-02
75%	4.023883e-02
max	inf

Table 19: Asset Growth Statistics

	CapEx_Growth
count	2.074560e+05
mean	inf
std	NaN
min	-7.433333e+01
25%	-1.573171e-01
30%	-9.192032e-02
50%	1.070024e-02
70%	1.660917e-01
75%	2.493195e-01
max	inf

Table 20: CapEx Growth Statistics

	ROE_z
count	5.275410e+05
mean	-4.884249e-18
std	9.997735e-01
min	-1.731062e+00
25%	-8.658411e-01
30%	-6.928205e-01
50%	0.000000e+00
70%	6.925534e-01
75%	8.658404e-01
max	1.731062e+00

Table 21: z(ROE) Statistics

	ROA_z
count	5.392300e+05
mean	-1.527707e-19
std	9.997784e-01
min	-1.731093e+00
25%	-8.658434e-01
30%	-6.926475e-01
50%	0.000000e+00
70%	6.926510e-01
75%	8.658434e-01
max	1.731093e+00

Table 22: z(ROA) Statistics

	COGS_to_Sales_z
count	1.335980e+05
mean	9.918612e-18
std	9.996931e-01
min	-1.730568e+00
25%	-8.657699e-01
30%	-6.926145e-01
50%	0.000000e+00
70%	6.926145e-01
75%	8.657699e-01
max	1.730568e+00

Table 23: z(COGS to Sales) Statistics

	PM_z
count	1.934370e+05
mean	-1.989295e-18
std	9.997880e-01
min	-1.731062e+00
25%	-8.658446e-01
30%	-6.926746e-01
50%	0.000000e+00
70%	6.926729e-01
75%	8.658384e-01
max	1.731062e+00

Table 24: z(Profit Margin) Statistics

	SoR_z
count	1.684980e+05
mean	-3.971483e-18
std	9.997566e-01
min	-1.730876e+00
25%	-8.658210e-01
30%	-6.924979e-01
50%	0.000000e+00
70%	6.926403e-01
75%	8.658213e-01
max	1.730884e+00

Table 25: z(Sales on Receivables) Statistics

	CFO_to_NI_z
count	1.931340e+05
mean	5.601299e-18
std	9.997877e-01
min	-1.731050e+00
25%	-8.658504e-01
30%	-6.926769e-01
50%	0.000000e+00
70%	6.926770e-01
75%	8.658505e-01
max	1.731050e+00

Table 26: z(CFO to Net Income) Statistics

	Payout_Ratio_z
count	1.612160e+05
mean	6.141431e-18
std	9.997456e-01
min	-1.746774e+00
25%	-8.777432e-01
30%	-6.963122e-01
50%	0.000000e+00
70%	6.959808e-01
75%	8.699964e-01
max	1.758178e+00

Table 27: z(Payout Ratio) Statistics

	DIss_z
count	1.774640e+05
mean	4.279136e-19
std	9.997718e-01
min	-1.730943e+00
25%	-8.658379e-01
30%	-6.925413e-01
50%	0.000000e+00
70%	6.925413e-01
75%	8.658379e-01
max	1.730963e+00

Table 28: z(Debt Issuance) Statistics

	EIss_z
count	1.834320e+05
mean	9.549642e-18
std	9.997792e-01
min	-1.731019e+00
25%	-8.658443e-01
30%	-6.926757e-01
50%	0.000000e+00
70%	6.926762e-01
75%	8.658406e-01
max	1.731019e+00

Table 29: z(Equity Issuance) Statistics

	Capex_to_DnA_z
count	1.883360e+05
mean	-5.208739e-18
std	9.997823e-01
min	-1.731020e+00
25%	-8.658498e-01
30%	-6.926148e-01
50%	0.000000e+00
70%	6.928224e-01
75%	8.658487e-01
max	1.731020e+00

Table 30: z(CapEx to DnA) Statistics

	Asset_Growth_z
count	1.875240e+05
mean	-2.533945e-18
std	9.997840e-01
min	-1.731035e+00
25%	-8.658397e-01
30%	-6.928204e-01
50%	0.000000e+00
70%	6.926788e-01
75%	8.658495e-01
max	1.731035e+00

Table 31: z(Asset Growth) Statistics

	CapEx_Growth
count	2.074560e+05
mean	inf
std	NaN
min	-7.433333e+01
25%	-1.573171e-01
30%	-9.192032e-02
50%	1.070024e-02
70%	1.660917e-01
75%	2.493195e-01
max	inf

Table 32: z(CapEx Growth) Statistics

III.2 Detecting Financial Stress Tables

	Emerging_markets
beta	1
t-stat	[-1.63]
verdict	Non-Stationary

Table 33: Emerging Markets OFR FSI DF Test

	VIX
beta	0.98
t-stat	[-5.74]
verdict	Stationary

Table 34: Credit OFR FSI DF Test

	Equity_valuation
beta	0.99
t-stat	[-3.59]
verdict	Non-Stationary

Table 35: Equity Valuation OFR FSI DF Test

	Fed_Rate
beta	1
t-stat	[-1.22]
verdict	Non-Stationary

Table 36: Fed Rate DF Test

	Funding
beta	1
t-stat	[-2.12]
verdict	Non-Stationary

Table 37: Funding OFR FSI DF Test

	KC_FSI
beta	0.96
t-stat	[-1.95]
verdict	Non-Stationary

Table 38: KC FSI DF Test

	OFR_FSI
beta	1
t-stat	[-1.94]
verdict	Non-Stationary

Table 39: OFR FSI DF Test

	Other_advanced_economies
beta	1
t-stat	[-2.01]
verdict	Non-Stationary

Table 40: Other Advanced Economies OFR FSI DF Test

	Safe_assets
beta	0.99
t-stat	[-3.56]
verdict	Non-Stationary

Table 41: Safe Assets OFR FSI DF Test

	STL_FSI
beta	0.97
t-stat	[-3.11]
verdict	Non-Stationary

Table 42: STL FSI DF Test

	TenY_ThreeM
beta	1
t-stat	[-1.88]
verdict	Non-Stationary

Table 43: TenY-ThreeM DF Test

	TenY_TwoY
beta	1
t-stat	[-1.37]
verdict	Non-Stationary

Table 44: TenY-TwoY DF Test

	TenYear
beta	1
t-stat	[-1.39]
verdict	Non-Stationary

Table 45: Ten-Year DF Test

	TenYear_Real
beta	0.97
t-stat	[-1.62]
verdict	Non-Stationary

Table 46: Ten-Year Real DF Test

	United_States
beta	1
t-stat	[-2.37]
verdict	Non-Stationary

Table 47: US OFR FSI DF Test

	Volatility
beta	1
t-stat	[-2.87]
verdict	Non-Stationary

Table 48: Volatility OFR FSI DF Test

	VIX
beta	0.98
t-stat	[-5.74]
verdict	Stationary

Table 49: VIX DF Test

	Emerging_markets_diff
beta	0.14
t-stat	[-51.61]
verdict	Stationary

Table 50: Emerging Markets OFR FSI (difference) DF Test

	Credit_diff
beta	0.28
t-stat	[-44.34]
verdict	Stationary

Table 51: Credit OFR FSI (difference) DF Test

	Equity_valuation_diff
beta	0.16
t-stat	[-50.64]
verdict	Stationary

Table 52: Equity Valuation OFR FSI (difference) DF Test

	Fed_Rate_diff
beta	-0.03
t-stat	[-73.4]
verdict	Stationary

Table 53: Fed Rate (difference) DF Test

	Funding_diff
beta	0.09
t-stat	[-54.03]
verdict	Stationary

Table 54: Funding OFR FSI (difference) DF Test

	KC_FSI_diff
beta	0.21
t-stat	[-10.44]
verdict	Stationary

Table 55: KC FSI DF (difference) Test

	OFR_FSI_diff
beta	0.17
t-stat	[-50.06]
verdict	Stationary

Table 56: OFR FSI (difference) DF Test

	Other_advanced_economies_diff
beta	0.12
t-stat	[-52.52]
verdict	Stationary

Table 57: Other Advanced Economies OFR FSI (difference) DF Test

	Safe_assets_diff
beta	-0.07
t-stat	[-63.84]
verdict	Stationary

Table 58: Safe Assets OFR FSI DF Test

	STL_FSI_diff
beta	-0.01
t-stat	[-27.18]
verdict	Stationary

Table 59: STL FSI (difference) DF Test

	TenY_ThreeM_diff
beta	0.09
t-stat	[-55.07]
verdict	Stationary

Table 60: TenY-ThreeM (difference) DF Test

	TenY_TwoY_diff
beta	0.03
t-stat	[-58.5]
verdict	Stationary

Table 61: TenY-TwoY (difference) DF Test

	TenYear_diff
beta	-0.01
t-stat	[-60.6]
verdict	Stationary

Table 62: Ten-Year (difference) DF Test

	TenYear_Real_diff
beta	-0.16
t-stat	[-15.17]
verdict	Stationary

Table 63: Ten-Year Real (difference) DF Test

	United_States_diff
beta	0.05
t-stat	[-56.36]
verdict	Stationary

Table 64: US OFR FSI (difference) DF Test

	Volatility_diff
beta	0.13
t-stat	[-51.75]
verdict	Stationary

Table 65: Volatility OFR FSI (difference) DF Test

Feature	VIF
VIXCLS	1.045838
DGS10	3.193758
DFF	1.009605
T10Y3M	2.539092
Equity_valuation	1.156758
OFR_FSI	18860.084156
Credit	3.867988
Funding	3.277216
Volatility	13.901856
United_States	4713.303207
Other_advanced_economies	5307.591924
Emerging_markets	201.961963
KCFSI	1.197171

Table 66: VIF All Relevant Indicators

Feature	VIF
VIXCLS	1.045836
DGS10	3.192366
DFF	1.009578
T10Y3M	2.539086
Equity_valuation	1.156755
Credit	3.856567
Funding	3.276792
Volatility	13.899750
United_States	8.154432
Other_advanced_economies	9.225518
Emerging_markets	2.784021
KCFSI	1.197160

Table 67: VIF All Indicators Minus Final OFR FSI

Feature	VIF
VIXCLS	1.044014
DGS10	2.802182
DFF	1.006797
T10Y3M	2.391619
Equity_valuation	1.154476
United_States	1.984246
Other_advanced_economies	1.935289
Emerging_markets	1.836370
KCFSI	1.155344

Table 68: VIF All Relevant Only Regional OFR FSIs

Feature	VIF
VIXCLS	1.045387
DGS10	2.891072
DFF	1.007017
T10Y3M	2.502995
Equity_valuation	1.154754
Credit	1.917536
Funding	1.257670
Volatility	1.414114
KCFSI	1.194641

Table 69: VIF All Relevant Only Category OFR FSIs

III.3 Investment Strategies Tables

Raw_FSI	Calm Quality	Calm MSCI World	Stressed Quality	Stressed MSCI World
Annualized_total_return	0.02	0.12	0.02	0.04
Volatility	0.05	0.09	0.09	0.17
Downside_volatility	0.03	0.06	0.06	0.11
Sharpe_Ratio	0.05	1.15	0.11	0.23
Information_Ratio	-0.89	NaN	-0.13	NaN
Sortino_Ratio	0.08	1.83	0.17	0.36
Beta	-0.13	1.00	-0.24	1.00
Pearson_Correlation	-0.24	1.00	-0.46	1.00
Spearman_Correlation	-0.24	1.00	-0.40	1.00
Max_Drawdown	0.08	0.08	0.24	0.59
Hit_Ratio	0.49	0.56	0.51	0.54
VaR_95%	0.00	0.01	0.01	0.02
Expected_Shortfall_95%	0.01	0.01	0.01	0.02
Downside_capture_ratio	-0.17	1.00	-0.26	1.00
Number of periods	684.00	684.00	2952.00	2952.00

Table 70: Raw FSI In-Sample Performance Metrics by Regime

	Benchmark	Quality	Strategy
Annualized_total_return	0.05	0.02	0.04
Volatility	0.16	0.08	0.09
Downside_volatility	0.10	0.05	0.06
Sharpe_Ratio	0.32	0.10	0.30
Information_Ratio	NaN	-0.21	-0.12
Sortino_Ratio	0.50	0.16	0.47
Beta	1.00	-0.23	-0.17
Pearson_Correlation	1.00	-0.45	-0.30
Spearman_Correlation	1.00	-0.38	-0.17
Max_Drawdown	0.59	0.24	0.24
Hit_Ratio	0.54	0.51	0.52
VaR_95%	0.01	0.01	0.01
Expected_Shortfall_95%	0.02	0.01	0.01
Downside_capture_ratio	1.00	-0.25	-0.12

Table 71: Raw FSI In-Sample Performance Metrics

Raw_FSI	Calm Quality	MSCI World	Stressed Quality	MSCI World
Annualized_total_return	0.01	0.08	0.06	0.03
Volatility	0.07	0.09	0.09	0.20
Downside_volatility	0.04	0.06	0.06	0.13
Sharpe_Ratio	-0.03	0.82	0.50	0.22
Information_Ratio	-0.62	NaN	0.02	NaN
Sortino_Ratio	-0.05	1.23	0.78	0.32
Beta	-0.10	1.00	-0.03	1.00
Pearson_Correlation	-0.13	1.00	-0.07	1.00
Spearman_Correlation	-0.19	1.00	-0.03	1.00
Max_Drawdown	0.16	0.17	0.17	0.34
Hit_Ratio	0.51	0.57	0.53	0.54
VaR_95%	0.01	0.01	0.01	0.02
Expected_Shortfall_95%	0.01	0.01	0.01	0.03
Downside_capture_ratio	-0.23	1.00	-0.06	1.00
Number of periods	620.00	620.00	939.00	939.00

Table 72: Raw FSI Out-Sample Performance Metrics by Regime

	Benchmark	Quality	Strategy
Annualized_total_return	0.05	0.04	0.07
Volatility	0.16	0.09	0.09
Downside_volatility	0.11	0.05	0.06
Sharpe_Ratio	0.34	0.32	0.63
Information_Ratio	NaN	-0.14	0.02
Sortino_Ratio	0.50	0.51	0.96
Beta	1.00	-0.04	0.10
Pearson_Correlation	1.00	-0.08	0.17
Spearman_Correlation	1.00	-0.08	0.32
Max_Drawdown	0.34	0.29	0.17
Hit_Ratio	0.55	0.52	0.54
VaR_95%	0.01	0.01	0.01
Expected_Shortfall_95%	0.02	0.01	0.01
Downside_capture_ratio	1.00	-0.10	0.19

Table 73: Raw FSI Out-Sample Performance Metrics

K_Means	Calm Quality	MSCI World	Stressed Quality	MSCI World
Annualized_total_return	0.02	0.08	0.02	-0.10
Volatility	0.06	0.12	0.16	0.32
Downside_volatility	0.04	0.08	0.11	0.20
Sharpe_Ratio	0.10	0.59	0.14	-0.21
Information_Ratio	-0.41	NaN	0.21	NaN
Sortino_Ratio	0.17	0.94	0.20	-0.34
Beta	-0.20	1.00	-0.26	1.00
Pearson_Correlation	-0.38	1.00	-0.52	1.00
Spearman_Correlation	-0.34	1.00	-0.51	1.00
Max_Drawdown	0.22	0.28	0.22	0.46
Hit_Ratio	0.51	0.55	0.54	0.51
VaR_95%	0.01	0.01	0.01	0.03
Expected_Shortfall_95%	0.01	0.02	0.02	0.04
Downside_capture_ratio	-0.23	1.00	-0.29	1.00
Number of periods	3148.00	3148.00	488.00	488.00

Table 74: k-Means In-Sample Performance Metrics by Regime

	Benchmark	Quality	Strategy
Annualized_total_return	0.05	0.02	0.07
Volatility	0.16	0.08	0.13
Downside_volatility	0.10	0.05	0.08
Sharpe_Ratio	0.32	0.10	0.51
Information_Ratio	NaN	-0.21	0.08
Sortino_Ratio	0.50	0.16	0.80
Beta	1.00	-0.23	0.35
Pearson_Correlation	1.00	-0.45	0.45
Spearman_Correlation	1.00	-0.38	0.71
Max_Drawdown	0.59	0.24	0.37
Hit_Ratio	0.54	0.51	0.55
VaR_95%	0.01	0.01	0.01
Expected_Shortfall_95%	0.02	0.01	0.02
Downside_capture_ratio	1.00	-0.25	0.61

Table 75: k-Means In-Sample Performance Metrics

K_Means	Calm Quality	MSCI World	Stressed Quality	MSCI World
Annualized_total_return	-0.02	0.06	0.41	-0.00
Volatility	0.08	0.11	0.12	0.33
Downside_volatility	0.05	0.07	0.06	0.22
Sharpe_Ratio	-0.34	0.51	2.78	0.13
Information_Ratio	-0.60	NaN	0.83	NaN
Sortino_Ratio	-0.49	0.77	5.54	0.19
Beta	-0.04	1.00	-0.04	1.00
Pearson_Correlation	-0.06	1.00	-0.11	1.00
Spearman_Correlation	-0.09	1.00	-0.04	1.00
Max_Drawdown	0.27	0.25	0.08	0.29
Hit_Ratio	0.52	0.56	0.53	0.52
VaR_95%	0.01	0.01	0.01	0.03
Expected_Shortfall_95%	0.01	0.01	0.02	0.04
Downside_capture_ratio	-0.08	1.00	-0.14	1.00
Number of periods	1331.00	1331.00	228.00	228.00

Table 76: k-Means Out-Sample Performance Metrics by Regime

	Benchmark	Quality	Strategy
Annualized_total_return	0.05	0.04	0.11
Volatility	0.16	0.09	0.11
Downside_volatility	0.11	0.05	0.07
Sharpe_Ratio	0.34	0.32	0.87
Information_Ratio	NaN	-0.14	0.32
Sortino_Ratio	0.50	0.51	1.37
Beta	1.00	-0.04	0.38
Pearson_Correlation	1.00	-0.08	0.54
Spearman_Correlation	1.00	-0.08	0.78
Max_Drawdown	0.34	0.29	0.17
Hit_Ratio	0.55	0.52	0.55
VaR_95%	0.01	0.01	0.01
Expected_Shortfall_95%	0.02	0.01	0.02
Downside_capture_ratio	1.00	-0.10	0.62

Table 77: k-Means Out-Sample Performance Metrics

BIC Values	n Components
67.55	1
143.18	2
223.40	3
304.69	4
386.17	5

Table 78: Gaussian Mixture Component BIC test

HMM	Calm Quality	 MSCI World	Stressed Quality	 MSCI World
Annualized_total_return	-0.00	0.12	0.09	-0.11
Volatility	0.06	0.11	0.13	0.25
Downside_volatility	0.03	0.07	0.09	0.16
Sharpe_Ratio	-0.26	0.93	0.58	-0.40
Information_Ratio	-0.83	NaN	0.52	NaN
Sortino_Ratio	-0.44	1.53	0.88	-0.61
Beta	-0.19	1.00	-0.25	1.00
Pearson_Correlation	-0.37	1.00	-0.49	1.00
Spearman_Correlation	-0.34	1.00	-0.45	1.00
Max_Drawdown	0.16	0.18	0.22	0.59
Hit_Ratio	0.50	0.55	0.54	0.52
VaR_95%	0.01	0.01	0.01	0.02
Expected_Shortfall_95%	0.01	0.02	0.02	0.03
Downside_capture_ratio	-0.22	1.00	-0.28	1.00
Number of periods	2688.00	2688.00	948.00	948.00

Table 79: HMM In-Sample Performance Metrics by Regime

	Benchmark	Quality	Strategy
Annualized_total_return	0.05	0.02	0.11
Volatility	0.16	0.08	0.12
Downside_volatility	0.10	0.05	0.07
Sharpe_Ratio	0.32	0.10	0.83
Information_Ratio	NaN	-0.21	0.27
Sortino_Ratio	0.50	0.16	1.32
Beta	1.00	-0.23	0.20
Pearson_Correlation	1.00	-0.45	0.28
Spearman_Correlation	1.00	-0.38	0.54
Max_Drawdown	0.59	0.24	0.23
Hit_Ratio	0.54	0.51	0.55
VaR_95%	0.01	0.01	0.01
Expected_Shortfall_95%	0.02	0.01	0.02
Downside_capture_ratio	1.00	-0.25	0.42

Table 80: HMM In-Sample Performance Metrics

HMM	Calm Quality	MSCI World	Stressed Quality	MSCI World
Annualized_total_return	0.00	0.08	0.23	-0.08
Volatility	0.08	0.11	0.13	0.32
Downside_volatility	0.05	0.07	0.07	0.21
Sharpe_Ratio	-0.06	0.67	1.58	-0.12
Information_Ratio	-0.57	NaN	0.68	NaN
Sortino_Ratio	-0.09	1.02	2.88	-0.18
Beta	-0.04	1.00	-0.04	1.00
Pearson_Correlation	-0.06	1.00	-0.10	1.00
Spearman_Correlation	-0.09	1.00	-0.04	1.00
Max_Drawdown	0.27	0.23	0.11	0.34
Hit_Ratio	0.52	0.56	0.52	0.51
VaR_95%	0.01	0.01	0.01	0.03
Expected_Shortfall_95%	0.01	0.01	0.02	0.04
Downside_capture_ratio	-0.10	1.00	-0.10	1.00
Number of periods	1317.00	1317.00	242.00	242.00

Table 81: HMM Out-Sample Performance Metrics by Regime

	Benchmark	Quality	Strategy
Annualized_total_return	0.05	0.04	0.10
Volatility	0.16	0.09	0.11
Downside_volatility	0.11	0.05	0.07
Sharpe_Ratio	0.34	0.32	0.83
Information_Ratio	NaN	-0.14	0.27
Sortino_Ratio	0.50	0.51	1.31
Beta	1.00	-0.04	0.35
Pearson_Correlation	1.00	-0.08	0.51
Spearman_Correlation	1.00	-0.08	0.76
Max_Drawdown	0.34	0.29	0.22
Hit_Ratio	0.55	0.52	0.55
VaR_95%	0.01	0.01	0.01
Expected_Shortfall_95%	0.02	0.01	0.02
Downside_capture_ratio	1.00	-0.10	0.60

Table 82: HMM Out-Sample Performance Metrics