Multidisciplinary portfolio management

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Multi-Asset Solutions Research Papers

First Sentier Investors

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Economic crises and endogenous events can cause significant turmoil in financial markets. Policymakers, investors, researchers and market historians know too well that large and sudden drawdowns are a feature of financial markets, providing exciting content for news and media services.

Uncertainty of outcomes is significantly elevated during events that cover broad economic impacts such as the Great Depression of 1932, the International Debt Crisis of 1982, the Russian Economic Crisis of 1992-97, the global financial crisis of 2007-09 and the flash crash of 2010. This also extends to geopolitical, political, and health-related events, such as the Cuban Missile crisis, the assassination of John F. Kennedy, the 9/11 terrorist attacks and the Covid-19 health-related pandemic.

Events like these can have direct impacts on the expected risk and return characteristics of various investment strategies. Wouldn't it be better to be able to understand the ever-evolving and changing nature of financial market relationships as they occur?

Traditional risk measures have often fallen short in the timely identification of these shifts. Understanding the limitations of financial models that use assumptions that we know to be flawed and incorporating a framework to assess market conditions that identify different regimes around events with fat tails and volatility clustering, can help circumnavigate changing market conditions.

Are we certain about uncertainty?

While there has been a research effort into quantifying, deconstructing and understanding the level, basis and origin of uncertainty, the literature remains in its infancy. The main body of work relates to measures of volatility and dispersion as gauges for uncertainty.

Existing research

Jurado et al. (2015) generalise uncertainty as, the conditional volatility of a disturbance that is unforecastable from the perspective of economic agents. A characteristic of economic or financial uncertainty is that it may have feedback loops or self-fulfilling characteristics. Several papers such as Bloom (2009), Bloom (2014), Bachmann and Bayer (2014), have already looked into how uncertainty impacts macroeconomic outputs and aggregates. While Stock and Watson (2012) finds that regarding the 2007-09 global financial crisis 'the main contributions to the decline in output and employment during the recession are estimated to come from financial and uncertainty shocks' rather than the contributions of productivity, monetary policy, and fiscal policy.

Meinen and Roehe (2017) use econometric unpredictability, understood as the conditional volatility of the unforecastable components of a broad set of macroeconomic variables. Diamond (2010) also points out that 'what's critical right now is not the functioning of the labor market, but the limits on the demand for labor coming from the great caution on the side of both consumers and firms because of the great uncertainty of what's going to happen next'.

Cascaldi-Garcia et al. (2020) summarised the existing research into risk, uncertainty and volatility measures. They divide uncertainty measures into three categories: economic policy, asset-market-based and Knightian, which disentangles risk from uncertainty. They cover both their calculations and whether the measures are available in real time. It should be noted that an important aspect of their review covers the definition of risk and how the measures, by construction and calculation, are limited to particular types of uncertainty and horizons.

> 'A central property of such complex systems is the possible occurrence of coherent large-scale collective behaviours with a very rich structure, resulting from the repeated nonlinear interactions among its constituents: the whole turns out to be much more than the sum of its parts.'
>
> — Didier Sornette (2002)

Our approach

We build on the existing research and offer a set of robust, comprehensive, but universally applicable, risk and uncertainty measures that can be applied to multivariate time series data such as macroeconomic variables and asset returns. We apply the analysis consistently across the broadest set possible; investigating the impact of uncertainty on asset classes, sectors, countries, and geographic regions as well as investment strategies and customised data and indices. We believe this helps us to understand the challenges faced by consumers, businesses, government policymakers and, in our case, investors.

Calculating uncertainty through the standard risk measures

Risk definitions can be trite, so we don't intend to do a deep dive on the oxford definitions of risk but to the layman, it is interesting to reflect on risk after the fact. That is, once a major event or shock occurs, was the following sequence a causal nexus? Or a structural shift in market conditions, such as a regime change?

Well, let's start with answering the causal nexus. While an improbable event did occur, we understood and acknowledged the possibility, relevance and impact.

From a pure mathematical view, a risk measure is the mapping of probability distributions to the characteristics of the underlying instrument. The aim of applying risk measures is to quantify the behaviour of the underlying uncertainty; usually focused on potential losses[1]. If we understand the probability of events occurring and their relationship with other variables, we have a good understanding of the risks.

One of the earliest measures of risk in the literature is standard deviation, which was used by Markowitz (1952) in his pioneering work in modern portfolio theory. Markowitz popularised these measures via mean-variance optimisation. It is a mathematical framework to show the likely fluctuation, potential returns, and the relationship between asset classes. While the early measure of risk is an elegant measure for mean-variance optimisation it doesn't distinguish between downside risk and upside reward. Risk measures such as standard deviation Value-At-Risk (VaR) and Conditional Value-At-Risk (CVaR) convey information about the expected outcomes of random variables.

In First Sentier Investors (2021) we demonstrated that traditional financial measures such as betas, volatilities and correlations are all time-varying; dispelling the assumption that these measures are constant. We also demonstrated that these variables are asymmetric. Both of these findings dispel the underlying assumptions in the Markowitz popularised mean-variance optimisation. That said, we do not want to throw the proverbial baby out with the bathwater as there are benefits of using simplifying assumptions. Separately, we discuss our asset allocation and portfolio optimisation framework in First Sentier Investors (2013).

A further wrinkle are the distribution assumptions. Commonly ex-ante risk statistics assume that asset returns have a normal or lognormal distribution. However, there is empirical evidence, as early as Mandelbrot (1963) that this assumption is flawed for financial return distributions. The combination of less skew and higher kurtosis indicates that there is a higher probability of negative outcomes than estimated. So, if the data has fat tails, using the standard distribution assumption for calculating risk measures, such as VaR and CVaR, will underestimate the outcomes in the left tail of the probability distribution.

1. While some measures focus on losses or less favourable outcomes, others are symmetric and do not distinguish.

Whilst we do not wish to derogate the usefulness and basis of these risk measures, they may not be reliable statistics in adverse environments of uncertainty.

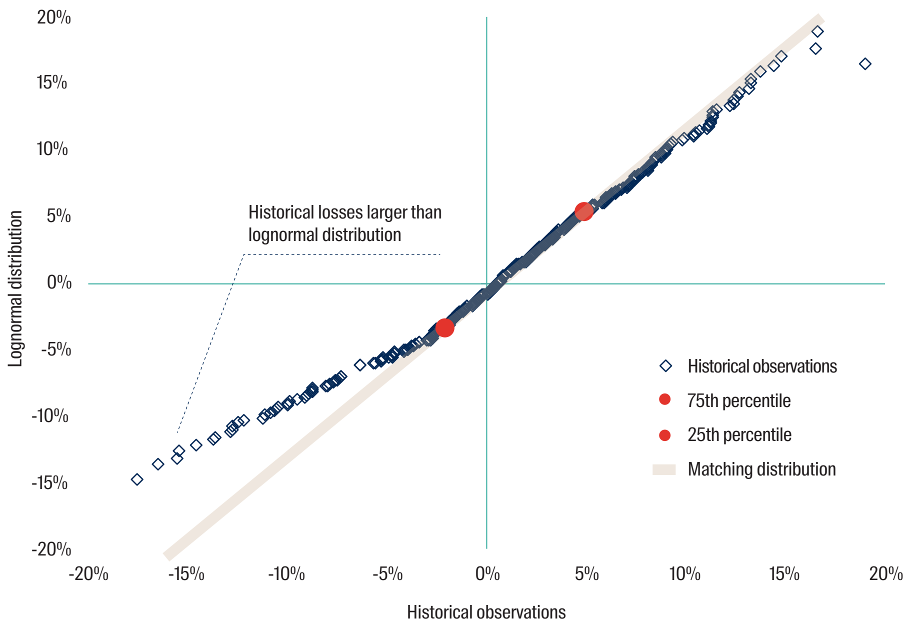
In addition to the assumption of normality, correlation matrices assume a linear relationship between two continuous variables, which is expressed as Pearson product-moment correlation. Not all assets exhibit linear relationships. For example short duration, low-quality corporate credit and payoffs related to options contracts all contain non-linear payoffs[2].

Finally, returns are generally assumed to be independent random variables. That implies that today's returns are independent of yesterday's returns. However, empirical evidence suggests that this assumption of independence is incorrect. Today's returns will be influenced by the size of yesterday's returns. If yesterday we observed a large movement, it will likely be followed by another large movement today also. This does not concern the direction of movement, however. This concept is known as 'volatility clustering' which is an important characteristic of financial data. As Mandelbrot (1963) described 'large changes tend to be followed by large changes, of either sign, and small changes tend to be followed by small changes.'

Figure 1 demonstrates an example of the mapping of the assumption of log-normally distributed returns vs historical observations using emerging market equities via a quantile-quantile plot[3].

As shown in the figure, history frequently has larger losses than modelled. This is undesirable when trying to estimate the risks and possible losses of a portfolio or investment strategy. We can also statistically reject the hypothesis that returns for emerging market equities are log-normal.

Figure 1: Quantile-quantile plot: History vs lognormal distribution



Source: First Sentier Investors, internal Propriety Models, MSCI Emerging Markets Index in local currency, data from 31 December 1987 to 30 June 2021.

2. This applies to all assets that contain fat tails or skewness in their return distributions; although highlighted by assets that experience defaults, such as corporate bonds with high credit risk.
3. A quantile-quantile plot is a graphical tool to help assess whether observations match a distribution assumption, such as lognormal. The scatterplot plots the quantiles against one another. If the data matches the distribution, the points will form a roughly straight line.

In the next section, we address how to evaluate whether a crisis, or unexpected event, requires a re-evaluation of portfolio assumptions. We introduce some new risk measures that provide colour and help quantify uncertainty.

Measuring uncertainty

In First Sentier Investors (2021) we examined foreign currency markets since 1979. We build on that foundation in this paper, providing a framework to examine individual securities, asset categories, investment subsectors and indeed even market factors, such as those identified by Fama and French (1992).

For simplicity and consistency, in this paper we use developed and emerging equity markets categorised by country. While this analysis can be applied to the complete history of financial markets, the focus of this paper is the 21st century, balancing modern history and relevance.

One dimensional risk

How big is big? Well, that depends. Answering that question requires a framework to consider the relativities of the dataset.

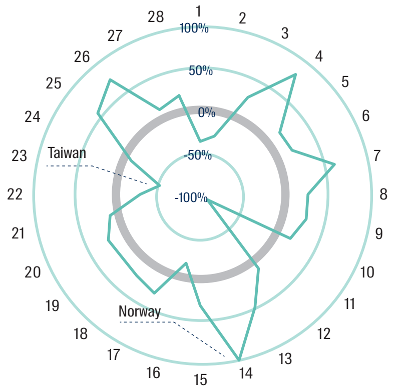
To measure the size of an observation we can use a standard score. This is commonly described as a z-score. It allows the comparison of an observation, in our case return, against the sample period. This provides a measure of the observation or raw score against the mean of the sample period accounting for the standard error or deviation of the data.

Assume an investor observes a return on an asset. A way to standardise, and assess the magnitude, is to assess the distance from the expected value based on the variations. This can be calculated on the population or sample data set.

We can also refer to percentiles to standardise the calculation regardless of the mean and variance of the dataset. For example, observations that are 2.33 standard deviations above the mean are at the 99th percentile.

Figure 2 shows the application of z-scores to equity markets, by country, as at 30 June 2021 using weekly data and a sample window of 104 observations (two years). As the visualisation highlights, we can see that Taiwan (22) had a return that was below the average of the sample period while Norway (14) had an above-average return compared to the sample period. Visualising the data via this method allows an effective overview of asset markets.

Figure 2: z-score distribution - global equity markets categorised by country



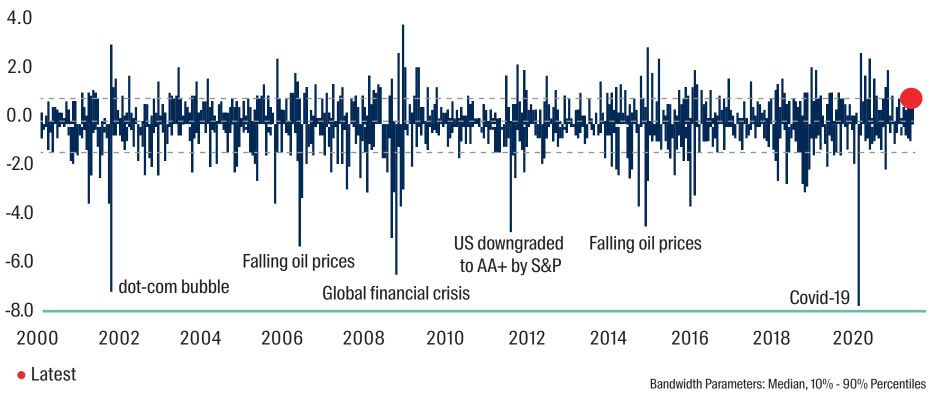
Grey polygon represents a value of zero

Reference	Name	Reference	Name
1	Australia	15	Russia
2	Brazil	16	Singapore
3	Canada	17	South Africa
4	China	18	South Korea
5	France	19	Spain
6	Germany	20	Sweden
7	Hong Kong	21	Switzerland
8	India	22	Taiwan
9	Italy	23	Thailand
10	Japan	24	Turkey
11	Malaysia	25	UK
12	Mexico	26	US
13	Netherlands	27	Portugal
14	Norway	28	Belgium

Source: First Sentier Investors, Internal Propriety Models, weekly data ending Friday as at 30 June 2021.

To further investigate the behaviour of a particular market, instead of viewing it as a point in time, we can visualise the data over time. Figure 3 shows the z-score for asset 14, Norway, since 2000. For a visualisation aid, the chart shows the 10th, 50th and 90th percentiles of the data. This provides additional context and insight to the most recent observation.

Figure 3: Norway equity returns: z-score



Source: First Sentier Investors, Internal Propriety Models, weekly data ending Friday, from 1 January 2000 to 30 June 2021.

We can zoom into particular periods that may be similar to the current environment, or worthy of further analysis. For example, we can look at embattled periods such as the onset of the Covid-19 health-related crisis. This can lead to further investigation of the behaviour of a particular market.

Timely identification of regimes and shifts in market behaviour

Although the historical calculation of non-normal behaviour is informative, it would be more useful to identify the precise moment when a regime shift occurs. Wouldn't it be good to know in advance whether we were in a bull or bear market? While we don't believe the analysis is cut-and-dried, we do believe we can improve on the analysis, for example of economic cycles, which commonly occurs through qualitative lenses that may be subject to errors and biases.

Regimes largely fall into three categories:

(1) the macroeconomic regime defined by growth, corporate profits, inflation and government monetary and fiscal policy;

(2) asset price fluctuations that are independent of the macroeconomic environment; and

(3) political and geopolitical impacts, as the world is not homogenous.

These phases exhibit certain properties that persist over days, weeks, months, or even years due to reasons such as, but not limited to, home biases, market structure, liquidity, cash flow requirements, forced hedging, behavioural biases, macroeconomic conditions, governmental regulations, and political events. The impact of these biases has been well researched and includes valuation[4] and momentum[5] based strategies as well as day-of-the-week effects[6].

This allows for a timely review of investment strategies, longer-term assumptions, such as volatilities and correlations, and the resulting allocations.

4. See Basu (1977), Rosenberg, Reid and Lanstein (1985), Fama and French (1992), and De Bondt and Thaler (1985, 1987).

5. Jegadeesh (1990) and Rouwenhorst (1997), Asness, Moskowitz and Pedersen (2013).

6. See Zhang et al (2017).

A portfolio built on long-term average market assumptions will become inappropriate when market behaviour shifts.

‘The error of optimism dies in the crisis, but in dying it gives birth to an error of pessimism. This new error is born not an infant, but a giant.’

- Arthur Cecil Pigou

If we can identify these shifts, the challenge is to identify the allocations or positions that would perform well in the new environment and to do so promptly.

Shifting sands

We now focus on the identification of Regime shifts. The aim is to remove the noise and change the information content to a probabilistic interpretation of market behaviour. This is helpful for two reasons: identifying when market behaviour is no longer ‘normal’, and secondly, to identify when markets return to ‘normal’.

To investigate a Regime shift or a breakdown in the existing relationships within the dataset(s) it would be helpful to find a generic model that can be applied to our dataset to identify temporal patterns, overcoming noise and uncertainty. The objective of the model is to provide transitional data; what Regime are we currently within and how likely are we to remain or shift.

For this, we use a Hidden Markov Model to infer something that we can’t directly observe. For example, if we have heart-rate data for a sample of the population we may be able to infer whether individuals are sleeping, awake or exercising at points in time without directly observing all the individuals. So, while we may not be able to observe directly the variable in which we are interested, there are several other important factors that we can observe to help inform our view.

To determine Regimes we universally apply a two-state Hidden Markov Model. Existing research into Regime models uses as few as two Regimes, including Nalewaik (2015) who proposes a two-state model for economic variables such as inflation and growth. Three states are commonly associated with financial markets. Four states are proposed by Guidolin and Timmermann (2005) to model the economic cycle of crash, recovery, slow growth, and bull market. We acknowledge that a two-state model could oversimplify the behaviour of financial markets, although given the options of simple or complex we recognise Occam’s razor[7]. The two-state model also matches our view of the extremes of market participants’ behaviour. For the most part market participants act rationally and try to maximise their risk-adjusted returns. However, there are times where high emotions or other drivers take control – leading to large scale uncertainty and panic.

This analysis builds a platform for investors and decision-makers to use when evaluating data. It provides a probabilistic assessment of both the state and transition. The application of Regimes is widely applicable. We will restrict the scope of this paper to using this framework in the context of Turbulence, Absorption and Similarity; relevant notions we will explore in the following sections.

7. Occam’s razor is a problem-solving principle that gives precedence to simplicity; among competing hypotheses, the one with the fewest assumptions should be selected.

Financial Turbulence

We examined z-scores for standardising and measuring an observation such as an asset return vs a sample data set. While this is a useful lens the vast majority of investment strategies, asset allocation decisions, and risk management techniques are all beset with multivariate time series; rather than a single time series[8]. As such, we are often interested in the relationship of multiple random variables such as returns, volatilities and correlations.

Investors are commonly focused on questions such as: 'is this time different'? Financial markets enjoy referring to the 'new normal', although it would be helpful to define the definition of 'normal' and distinguish in real time whether or not this is a deviation from past experiences. To do this, it would be beneficial to have a formal model to arrive at such conclusions. Thus we need to determine an appropriate measure of abnormality in data for the identification of outliers.

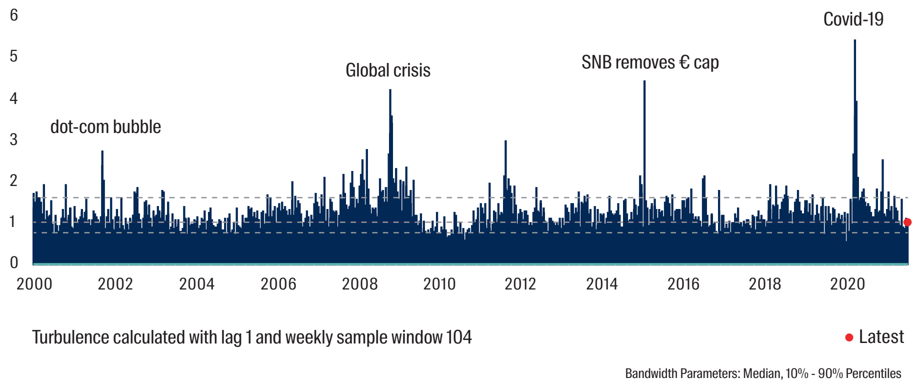
As history would have it, we have encountered this problem in a different class of problems. Mahalanobis (1927, 1936) defined a distance measure that was prompted by the requirement to compare the similarities, or lack thereof, of human skulls. We use this measure to calculate the degree of uncharacteristic behaviour within financial markets, capturing extreme price movements and changing relationships. Kritzman (2010) coined the application of this measure to financial markets 'Turbulence'[9]. We believe this represents an appropriate and vernacularly intelligible description of the distance measure when applied to financial markets and will refer to the Mahalanobis distance as Turbulence for the remainder of the paper.

The Mahalonobis distance is essentially a multivariate extension of the z-scores we previously calculated. If we simply sum the squares of z-scores over a full universe, we move from a z-score to a (normalised) squared Euclidean distance[10] measure. However, that would not account for any relationships between the variables such as correlations. By accounting for correlations we arrive at the squared Mahalanobis[11] distance.

One of the most attractive features of the Mahalanobis distance measure is that it summarises the information on unusual behaviour across all assets into a single quantifiable metric. Thus providing the user with a model for multivariate unusualness in financial market data.

Figure 4 shows Turbulence in equity markets, categorised by countries, highlighting the unusual behaviour in 2008, 2015 and 2020.

Figure 4: Global equity market Turbulence



Source: First Sentier Investors, Internal Propriety Models, weekly data ending Friday, from 1 January 2000 to 30 June 2021.

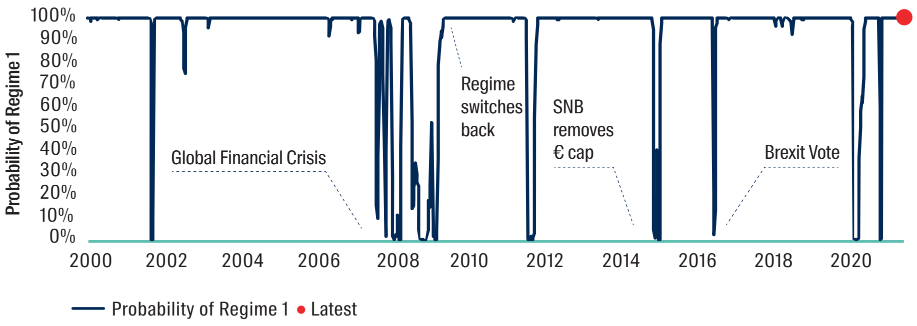
8. A time series is a sequence such as $X = (x_1, x_2, \dots, x_m)$ of observed data over time.
9. Turbulence is calculated as Mahalanobis distance of recent sets of returns compared to their history.
10. Euclidean distance(x,y) = $\sqrt{(x-y)^T (x-y)}$
11. Mahalanobis distance(x,y) = $\sqrt{(x-y)^T \mathrm{cov}(x,y)^{-1} (x-y)}$

This approach can be applied to a variety of datasets. We routinely examine key economic variables such as inflation and economic growth. We can also divide financial assets into geographical regions, sectors, and decompose fixed income markets into segments such as tenor.

Figure 5 provides a graphical representation of the outcome of applying the two-state Regime model, building on our example of financial Turbulence in equity markets, categorised by countries.

We posit that financial market activity can be characterised at any point of being in one of two states. We visualise the model by showing the probability that we are in Regime 1.

Figure 5: Regime probability: global equity market Turbulence



Latest Regime probablilities: Regime 1: 100%, Regime 2: 0%
Regime 1: Low Average, Low Volatility, Persistence: 98.3%
Regime 2: High Average, High Volatility, Persistence: 84.2%
Turbulence calculated with lag 1 and weekly sample window 104

Source: First Sentier Investors, Internal Propriety Models, weekly data ending Friday, from 1 January 2000 to 30 June 2021.

Figure 6 shows the latest probabilities and transition matrix. The model calculates the probabilities of being in either Regime. We can see that the latest estimated probability is 100% for Regime 1 and 0% for Regime 2.

The transition matrix provides the probability of remaining within, or switching Regimes. The persistence of Regime 1 is 98.3%. The complement is that there is a 1.7% chance of switching to Regime 2. Whereas Regime 2 has an 84.2% persistence and 15.8% chance of switching to Regime 1.

Of the two-state model, we can see that Regime 1 has a lower average, and lower volatility of Turbulence. Whilst in our formulation we may have assumed that our Regimes may correspond to these statistics as we were looking for 'normal market conditions' and 'periods of stress' the states can correspond to 'higher average with lower volatility,' and 'lower average with higher volatility'. The two-state Hidden Markov Model does the determination.

Figure 6: Transition matrix and statistics: global equity market Turbulence

Latest Probabilities	
Regime 1	Regime 2
100.0%	0.0%

Global EQ: Turbulence Regime	Transistion Matrix	
	Regime 1	Regime 2
Regime 1	98.3%	1.7%
Regime 2	15.8%	84.2%

	Statistics	
	Regime 1	Regime 2
Average	111.5%	227.5%
Volatility	28.5%	125.7%

Regime 1: Low Average, Low Volatility, Persistence: 98.3%
Regime 2: High Average, High Volatility, Persistence: 84.2%

Source: First Sentier Investors, Internal Propriety Models, data as at 30 June 2021.

Again it is important to recognise that we are using financial Turbulence as the input. We are not identifying cheap versus rich valuations in asset markets. Valuation is a very different topic from changing market behaviour and we shouldn't conflate the two. So far we have only investigated equity markets via country. As already stated, the benefits can be extended to different asset classes, investment subsectors and indeed even market factors, such as those identified by Fama and French (1992).

Covid-19 case study: filtering historical data

Covid-19 was an unprecedented health and economic crisis. In the first half of 2020, we completed our regular asset allocation review for our Multi-Asset portfolios. The quantum of unknowns at the time made meaningful analytical analysis difficult. As shown in figure 5, as well as subsequent figures, Covid-19 instigated an identifiable Regime shift.

As part of the asset allocation review, we filtered history to examine asset class characteristics applying Regimes to the financial Turbulence across equities, fixed income, currency and commodities. Regime 2 corresponds with periods of high uncertainty, which was appropriate given the ongoing health pandemic.

We utilised the asset class volatilities and correlations during these periods to optimise the portfolios allocations. The resulting portfolios were robust; as they incorporated the higher volatilities, tighter (downside) correlations and as such were less reliant on experiencing 'normal' or 'average' conditions.

Absorption: measuring diversification and potential for contagion

In a utopian investment world, we would be able to identify all the factors that drive potential performance and risks. This would provide us with a much better macro-level view of ex-ante risk decomposition. Many investors have had the right thesis, but the wrong positions.

The holy grail of asset allocation is the identification of uncorrelated, positive return generating, compounding assets over time. So being able to find uncorrelated return and risk drivers would be significantly meaningful. Or in a risk management context, the reverse would be informative: how unified are my exposures?

The higher the Absorption, the more concentrated the risks. This makes capital markets fragile, increasing the likelihood of shocks propagating through the capital markets as fewer factors drive returns.

Numerous studies have published suggested measures of financial integration or segregation[12]. For example, Forbes and Rigobon (1999) investigate shifts in the variance-covariance matrix to test for contagion, whereas Eiling and Gerard (2014) calculate the extent of integration using global and regional factors. Pukthuanthong and Roll (2009) put forward an R-squared integration measure by regressing country returns on the prior calendar year's principal components.

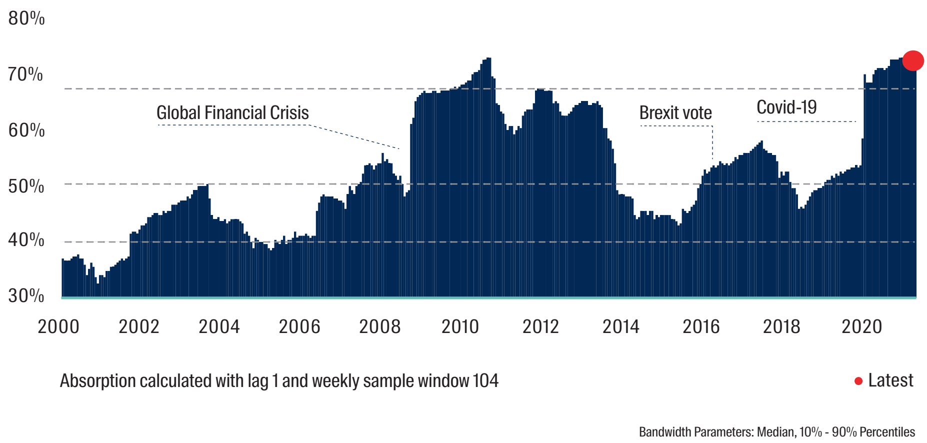
We use principal components analysis (PCA) to decompose the variation in returns into orthogonal, that is uncorrelated, factors that explain as much of the variation in returns as possible. This helps in avoiding model overfitting, especially when there is a large number of variables in the dataset. It reduces the number of dimensions so that it can be easily visualised.

This quantifies the degree to which performance is explained by the first n factors. Kritzman et al. (2010) used the moniker of 'Absorption' to describe the application of PCA to financial market returns. We prefer 'Brittleness' as a more intuitive description, although retain 'Absorption' to align terminology.

The quantum these n factors can explain is called the Absorption ratio.

Figure 7 shows the Absorption over time for equities, demonstrating how much the first two principal components drive asset returns and ultimate risks. In March 2020, during the onset of the global Covid-19 health pandemic, the Absorption ratio increased significantly; from a level close to the median to above the 90th percentile. As the Absorption ratio increases capital markets become less resilient, implying that isolated shocks are more likely to cascade and become terminal.

Figure 7: Absorption ratio - global equity markets



Source: First Sentier Investors, Internal Propriety Models, weekly data ending Friday, from 1 January 2000 to 30 June 2021.

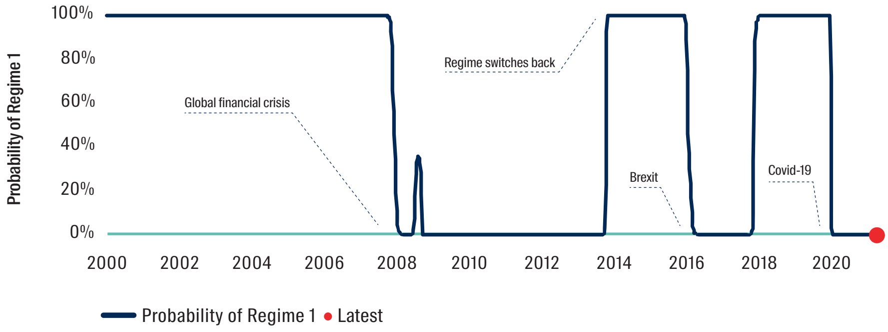
12. Segregation is the opposite of integration.

When capital markets become coupled, broad portfolio protection strategies and tail risk strategies are likely to become meaningful.

Taking the Absorption ratio, we again use Regime shifts to provide us with a quantitative measure of the unification of financial markets. This provides us with another layer of capital market information. Figure 8 identifies a Regime shift from Regime 1 to Regime 2 on 20th March 2020. Regime 2 is characterised by a high average Absorption ratio and as at the end of June 2021 we remain in Regime 2. This indicates that movements within equity markets are currently highly unified and providing little diversification.

The figure also allows us to identify the onset of historical events such as the global financial crisis, where equity markets remained unified until 2014. In the eye of the storm, everything becomes a burden (or saviour in the case of insurance).

Figure 8: Regime probability - global equity Absorption



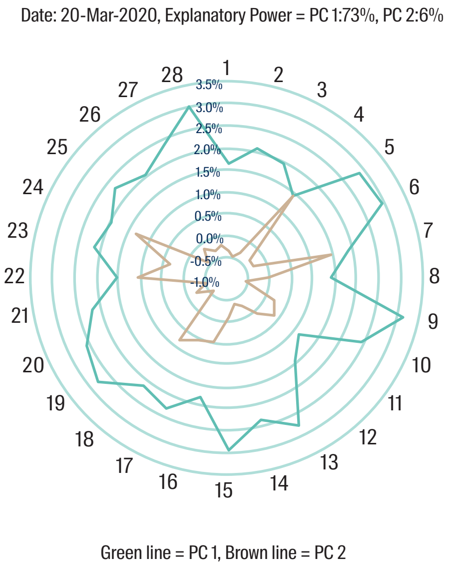
Regime probablilities at 25-Jun-2021: Regime 1: 0%, Regime 2: 100%
Regime 1: Low Average, High Volatility, Persistence: 99.7%
Regime 2: High Average, Low Volatility, Persistence: 99.6%
Absorption calculated with lag 1 and weekly sample window 104

Source: First Sentier Investors, Internal Propriety Models, weekly data ending Friday, from 1 January 2000 to 30 June 2021.

In addition to visualising the total variance explained by n principal components, we normalise the Eigenvectors[13] to avoid any differences in loading and to provide a better representation of variables in two-dimensional figures. Figure 9 shows the principal component composition by asset as at 20 March 2020. The first principal component is the green line by time series (asset), while the second principal component is shown in the brown line. It illustrates that 64% of the variance was being driven by the first component with only 6.5% from the second component.

13. Since the Eigenvectors indicate the direction of the principal components, we multiply the original data by the eigenvectors to re-orient our data onto the new axes.

Figure 9: Absorption - principal component composition



Reference	Name	Reference	Name
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3	Canada	17	South Africa
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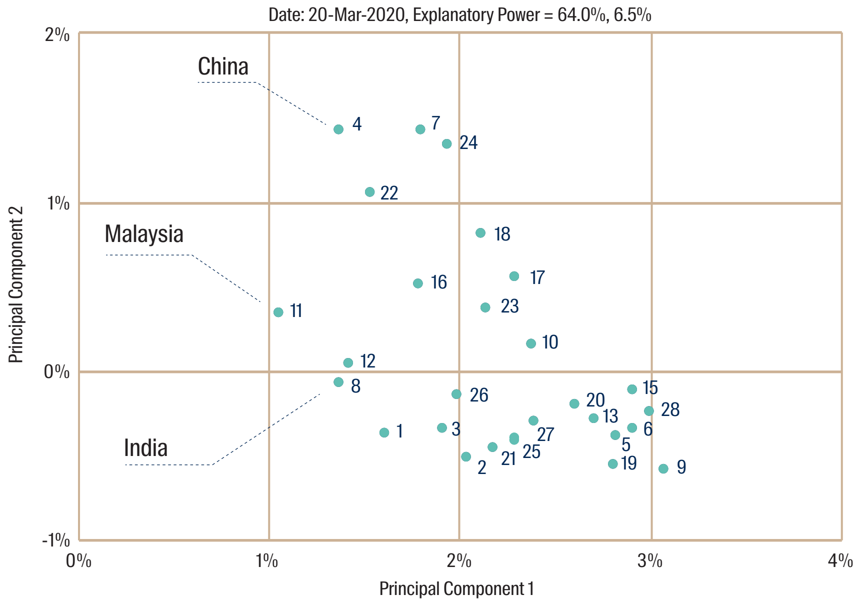
6	Germany	20	Sweden
7	Hong Kong	21	Switzerland
8	India	22	Taiwan
9	Italy	23	Thailand
10	Japan	24	Turkey
11	Malaysia	25	UK
12	Mexico	26	US
13	Netherlands	27	Portugal
14	Norway	28	Belgium

Source: First Sentier Investors, Internal Propriety Models, data as of 20 March 2020.

As illustrated in Figure 10, the same data can also be visualised in a scatter plot with the principal components listed on the x and y-axis. This is the more common visualisation as it is easy to see the series that is the most, or least, influenced by the independent factors. We can see that the returns, as at 20 March 2020, of Malaysia (11), China (4) and India (8) are least explained by the first principal component.

Figure 10: Principal component composition



Source: First Sentier Investors, Internal Propriety Models, data as of 20 March 2020.

We are more similar than we are different

So far, we have introduced a range of measures to monitor and measure behaviour within a multivariate time series. We now introduce a new measure which we call Similarity. We use this measure to compare the 'similarity' of an observation with a sample period. That is, 'how close is the current observation to the past'? We can use this for a measure of time series or in our case asset *i* and can be aggregated into an overall measure for the multivariate time series.

Cassisi et al. (2012) present data dimensionality reduction techniques. We build on this approach. We again use a distance notion to mathematically describe how close the multivariate time series is versus the past or sample data.

A percentile rank measure methodology is utilised, which has multiple benefits. It provides a measure between the bounds of zero and one. Additionally, these ranks can be calculated directly based on ranking the sample data without any distribution assumption. Alternatively, one can calculate the expected value and standard deviation of the sample data and assume normality or log-normality of the data to calculate the ranks through their respective cumulative distributions. The distribution of Similarities has characteristics independent of the chosen distribution, even though actual Similarity may differ.

By calculating the percentile rank for all data points we can compare the most recent data point, or observation of interest, with all observations in the sample period. The sum of the absolute difference between the observation and the time series is the measure of how non-similar the data is from history. By subtracting this measure from a value of one it provides the Similarity measure[14].

We can also weigh the components within the multivariate time series to provide an aggregate Similarity measure. This is appropriate if we are examining portfolio components. This allows the application of a weighting scheme to the individual Similarities. This method is prudent as it looks at each component of Asset$_i$ in the multivariate time series and sums the differences.

Since the Similarity S_{t_O} (t) for the overall portfolio P is defined as the weighted sum of these individual Similarities there is no diversification between the assets A_i used. This way the situation is avoided that on the overall P level there may be a seemingly high level of Similarity, whereas the components are quite different[15].

Using quarterly return observations of countries within the global equity universe, we can compare the latest observation of asset *i* with its history. This gives insight into high and low Similarity periods with the latest output, the reference date of 30 June 2021.

14. The Similarity for time series A_i based on the latest observation (*time t_0*) is expressed as:
$S^i(t) = 1 - \Delta^i_{t_0}(t)$, where: $\Delta^i_{t_0}(t) = |\, PercentileRanks^i_{t_0} - PercentileRanks^i_t \,|$
These individual asset similarities $S^i_{t_0}(t)$ total to a metric for the overall similarity $S_{t_0}(t)$ of the portfolio at time t_0 for all t.

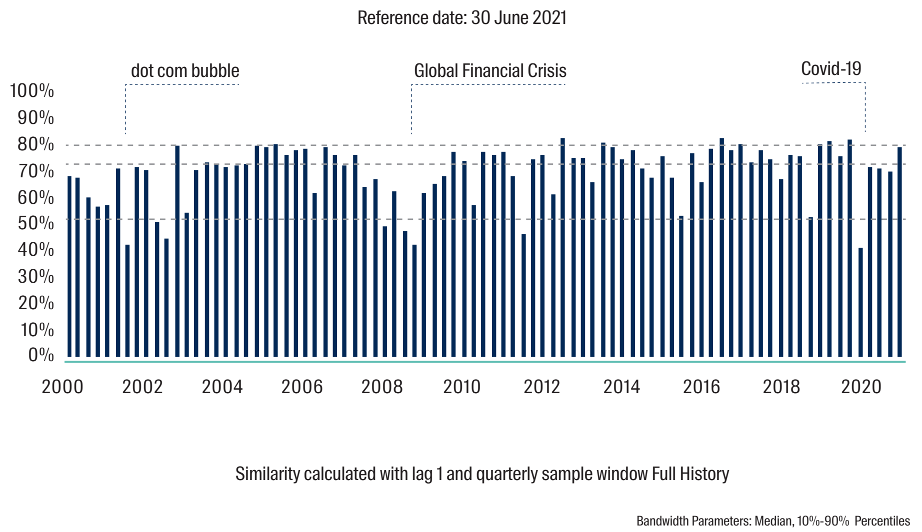
$$S_{t_0}(t) = 1 - \sum_{i=1}^{m} w_i(t)\,\Delta^i_{t_0}(t)$$

For examples in this paper and our investment process, the multivariate time series contains asset returns.

15. The alternative method is where one does not look at individual asset Similarities but focuses on the Similarity of the weighted sum of observations.

Figure 11 shows the historical Similarities, using 31 March 2000 to 31 March 2021[16] as the sample period. We use Similarity to identify the most or least comparable historical period to the reference date. For example, we can see that markets were the most similar to the existing state for the period ending September 2016, while the least similar period to the reference date was March 2020. This coincides with the onset of the Covid-19 health-related pandemic and reinforces the considerations in the related case study.

Figure 11: Similarity - global equity markets



Source: First Sentier Investors, Internal Propriety Models, quarterly data from 31 March 2000 to 31 March 2021.

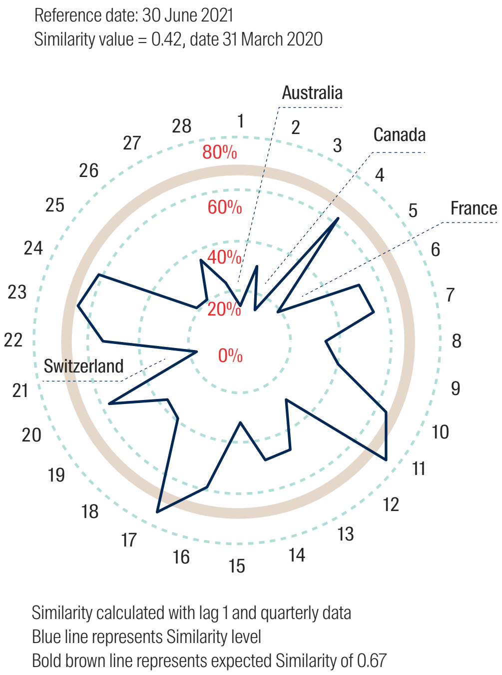
We can further examine periods and variables of interest. It may be helpful to examine the multivariate time series at a point in time or visualise an asset's Similarity across time. It should be noted that the expected value of the Similarity measure is 2/3[17], that is if we have independent uniform random variables.

16. As referenced in the chart we use a lag of one period to exclude the reference date from the sample period.

17. $E(\text{Similarity}) = 1 - E(|X-Y|) = 2/3$, using the triangular distribution $|X-Y|$, on interval $[0, 1]$ with mode=0.

Figure 12 shows the multivariate time series as at March 2020 to allow the examination of individual asset Similarities. This is visualised in the polygon in figure 12. Notably, Australia (1), Canada (3), France (5) and Switzerland (21) had Similarity values less than 0.2.

Figure 12: Similarity - global equity markets categorised by country

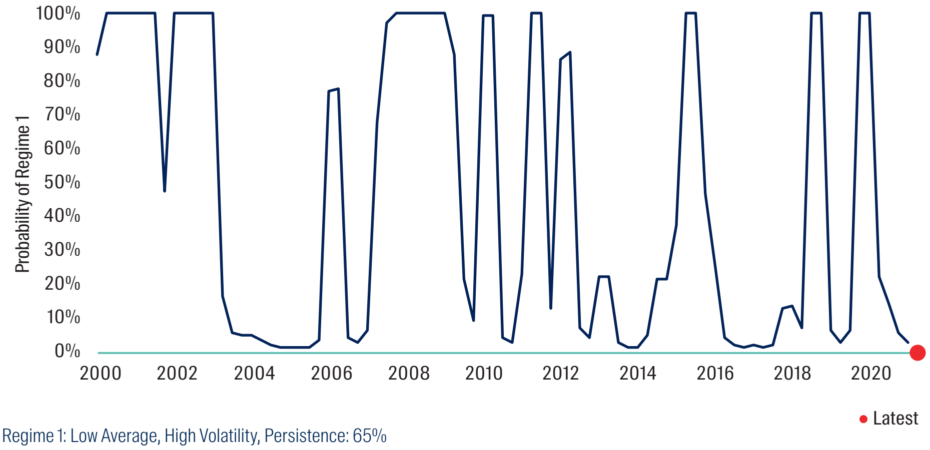


Reference	Name	Reference	Name
1	Australia	15	Russia
2	Brazil	16	Singapore
3	Canada	17	South Africa
4	China	18	South Korea
5	France	19	Spain
6	Germany	20	Sweden
7	Hong Kong	21	Switzerland
8	India	22	Taiwan
9	Italy	23	Thailand
10	Japan	24	Turkey
11	Malaysia	25	UK
12	Mexico	26	US
13	Netherlands	27	Portugal
14	Norway	28	Belgium

Source: First Sentier Investors, Internal Propriety Models, quarterly data as at 31 March 2020.

We can again, use the time series of Similarities in the Regime framework to create a 'Similarity-Regime'. This gives insight into high and low Similarity periods, with the reference date of 30 June 2021, and is shown in Figure 13 below. Regime 1 represents periods that have low Similarity with reference period, while Regime 2 represents periods with high Similarity. Statistical verification of these changes in market characteristics can reduce the reliance on long-run assumptions and assist in determining whether portfolio allocations and risk exposures are appropriate for the given environment.

Figure 13: Regime probability - global equity Similarity



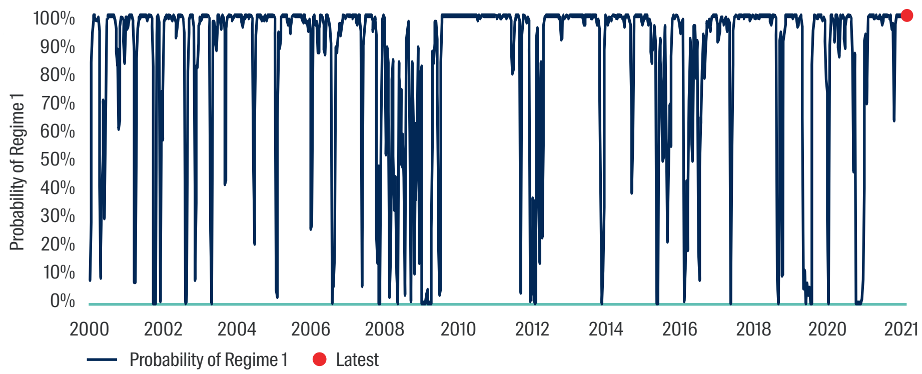
Regime 1: Low Average, High Volatility, Persistence: 65%
Regime 2: High Average, Low Volatility, Persistence: 67%
Similarity calculated with lag 1 and quarterly sample window Full History

Source: First Sentier Investors, Internal Propriety Models, quarterly data from 31 March 2000 to 30 June 2021.

Investment Signal case study: performance characteristics in different Regimes

In First Sentier Investors (2014) we discuss the ability to generate additional returns, or abate portfolio risks, by reallocating capital when capital markets deviate from 'fair value'. We do this via our Dynamic Asset Allocation process, which is informed by our Investment Signals. We utilise the Regime framework described in this paper to provide analysis across a variety of measures such as Turbulence, Absorption and Similarity to examine the efficacy of Investment Signals. Figure 14 shows the outcome of applying Regimes to the financial Turbulence across equities, fixed income, currency and commodities. Regime 1 represents the more frequently occurring 'normal' market conditions. We apply Regime modelling to all of our Investment Signals to examine their characteristics during the altered Regimes.

Figure 14: Regime probability - global asset market Turbulence



Regime probablilities at 25-Jun-2021: Regime 1: 99.3%, Regime 2: 0.7%
Regime 1: Low Average, Low Volatility, Persistence: 91%
Regime 2: High Average, High Volatility, Persistence: 59%
Turbulence calculated with lag 1 and weekly sample window 104

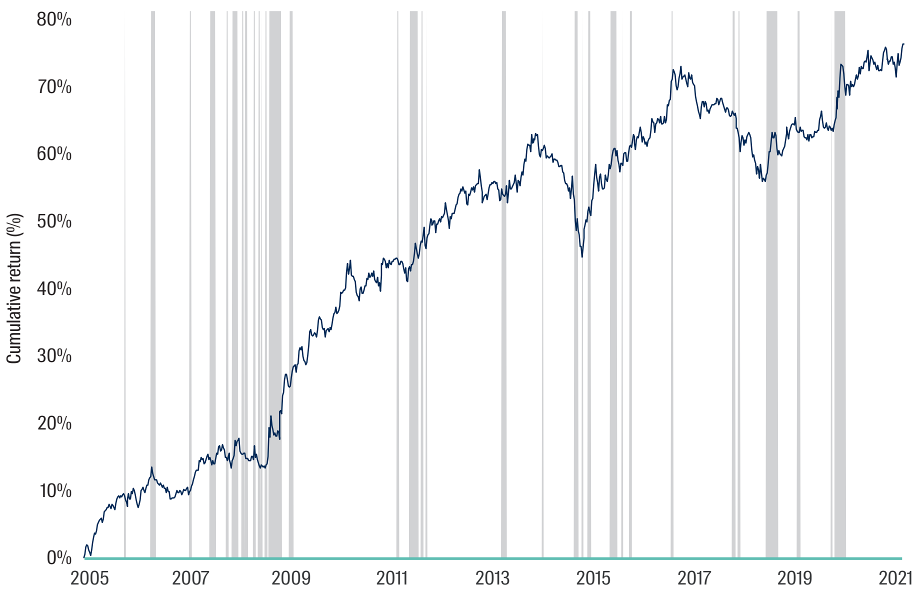
Source: First Sentier Investors, Internal Propriety Models, weekly data ending Friday, from 1 January 2000 to 30 June 2021.

We find that investment strategies exhibit different behaviours between Regimes. For example, our Economic Surprise Investment Signal for currencies has higher average returns, with moderately higher volatility in Regime 2. The outcome is an improved information ratio in Regime 2.

Figure 15 shows the cumulative performance of the Economic Surprise Investment Signal, with the shaded sections representing Regime 2. Whilst the majority of time is spent in Regime 1, Regime 2 represents superior risk-adjusted returns.

Our experience is that Investment Signals that utilise a valuation methodology perform better in Regime 1 as they respond slower to market sentiment and changing conditions, while Investment Signals that use market pricing as inputs can benefit switching to Regime 2.

Figure 15: Economic Surprise (Currencies) - Investment Signal



Source: First Sentier Investors, Internal Propriety Models, weekly data ending Friday, from 21 January 2005 to 30 June 2021.

Conclusion

In this paper, we introduced a range of robust comprehensive, but generically applicable, risk and uncertainty measures that can be applied to macroeconomic data, cross-sectional price and return data across sectors, markets, and geographic regions and can be applied to customised data and indices if, and where, relevant.

The application of this research is wide-ranging and a key part of our investment process.

Research integration

This paper covered the design of the measures that we use to determine the 'state' of economic and financial markets. This allows us to empirically verify whether portfolios, asset allocations, investment strategies and the risk management framework is appropriate for the given environment and to be able to optimise our positioning accordingly.

We use the analytical method of evaluating Turbulence, Regimes and Similarity to aid our Dynamic Asset Allocation and investment strategies. For example, our investment strategies that utilise rotational preferences within an asset class are examined to determine whether they exhibit clear and distinct Regime preferences or behaviour. This provides an additional layer of understanding and helps verify whether strategies are additive within the portfolio, based on their empirical characteristics in different environments.

We intend to utilise this framework to demonstrate the practical application to the portfolios and proprietary Investment Signals in future research; specifically the upcoming paper on portfolio hedging and tail risk management.

Glossary

Absorption ('brittleness of the market')

Absorption is the sum of the first few Principal Components and represents the total explanatory power of the most dominant independent factors. Its level is a measure of the 'lack of depth' of the volatility in the market and can therefore be interpreted as a market brittleness indicator.

Average Correlation ('diversification in the market')

Average Correlation is the average of all correlations in the market based on a historical sample period and can be interpreted as an indicator for the aggregate level of diversification inherent in the market.

Conditional Value-At-Risk or CVaR ('average shortfall')

Conditional Value-At-Risk (CVaR) is the mean expected loss given the loss occurs at or below the n-percentile. Expanding on the portfolio VaR example above, if the portfolio has a 1-year CVaR of 10% at the 99% confidence, it implies that the average loss in the worst 1% of scenarios is 10%.

Lognormal distribution

A continuous distribution in which the logarithm of a variable has a normal distribution.

Regime ('state of the world')

The Regime concept is a two-state Hidden Markov Model, where two different distributions are determined that best fit a given time series. For each historical date, probabilities are derived to be drawn from either of them. This concept enables categorising the current 'state of the world' or 'Regime' and can also be used as an indicator of structural change thereof.

Similarity ('historical similarity decomposition')

Using a historical sample period, the Similarity concept is based on the normalised Manhattan-distance between the rank of the latest element of a multivariate time series and its historical ranks. For each historical element, a level of Similarity with the latest element is derived. This concept enables 'decomposing' the latest element in historical elements, where the historical weights are based on the level of Similarity.

Standard deviation ('dispersion from average')

Standard deviation is the measure of the dispersion of a set of data from its mean. The more spread apart the data, the higher the deviation. This is calculated by taking the square root of variance where variance is the average of the squared differences of each data point from the mean. A standard deviation of close to zero means that the data points tend to be very close to the mean whereas a large standard deviation indicates that data points are spread across a wide range of values.

Turbulence ('normality of the market')

Turbulence is the Mahalanobis-distance of the latest element in a multivariate time series to the centre of the cloud of the same series over a sample period. Its level is used to assess how different that latest element is from the historical average and can be used to assess the 'normality' of the market. Turbulence can be interpreted as a multivariate directionless version of a z-score.

Value-at-Risk or VaR ('shortfall')

Value-at-Risk (VaR) is the expected loss given a probability, defined as the confidence level, over a given time horizon. For example, if a portfolio has a 1-year VaR of 5% at the 99% confidence level, it is implied that, under normal trading conditions, the portfolio manager can be 99% confident that its portfolio will not decrease more than 5% in one year. The confidence level also represents the return from the distribution at the n-percentile where n = 1 – confidence level.

Z-score ('standard score')

Z-scores are the difference of each variable from its average, measured in units of standard deviations.

Appendix

The table below provides a list of equity markets, by country, that are used within the figures.

Reference / Asset number	Name
1	Australia
2	Brazil
3	Canada
4	China
5	France
6	Germany
7	Hong Kong
8	India
9	Italy
10	Japan
11	Malaysia
12	Mexico
13	Netherlands
14	Norway
15	Russia
16	Singapore
17	South Africa
18	South Korea
19	Spain
20	Sweden
21	Switzerland
22	Taiwan
23	Thailand
24	Turkey
25	UK
26	US
27	Portugal
28	Belgium

References

Asness, C. S., Moskowitz, T. J., & Pedersen, L. H. (2013). Value and momentum everywhere. The Journal of Finance, 68(3), 929-985. https://doi.org/10.1111/jofi.12021

Bachmann, R., & Bayer, C. (2014). Investment dispersion and the business cycle. American Economic Review, 104(4), 1392-1416. https://doi.org/10.1257/aer.104.4.1392

Basu, S. (1977). Investment performance of common stocks in relation to their price-earnings ratios: A test of the efficient market hypothesis. The Journal of Finance, 32(3), 663-682. https://doi.org/10.1111/j.1540-6261.1977.tb01979.x

Bloom, N. (2009). The impact of uncertainty shocks. Econometrica, 77(3), 623-685. https://doi.org/10.3982/ecta6248

Bloom, N. (2014). Fluctuations in uncertainty. Journal of Economic Perspectives, 28(2), 153-176. https://doi.org/10.1257/jep.28.2.153

Cascaldi-Garcia, Danilo, Cisil Sarisoy, Juan M. Londono, John Rogers, Deepa Datta, Thiago Ferreira, Olesya Grishchenko, Mohammad R. Jahan-Parvar, Francesca Loria, Sai Ma, Marius Rodriguez, and Ilknur Zer (2020). What is Certain about Uncertainty?, International Finance Discussion Papers 1294. Washington: Board of Governors of the Federal Reserve System, https://doi.org/10.17016/IFDP.2020.1294.

Cassisi, C., Montalto, P., Aliotta, M., Cannata, A., & Pulvirenti, A. (2012). Similarity measures and dimensionality reduction techniques for time series data mining. Advances in Data Mining Knowledge Discovery and Applications. https://doi.org/10.5772/49941

De Bondt, W. F., & Thaler, R. H. (1985). Does the stock market overreact? The Journal of Finance, 40(3), 793-805. https://doi.org/10.1111/j.1540-6261.1985.tb05004.x

De Bondt, W. F., & Thaler, R. H. (1987). Further evidence on investor overreaction and stock market seasonality. The Journal of Finance, 42(3), 557-581. https://doi.org/10.1111/j.1540-6261.1987.tb04569.x

Diamond, P. (2010). Nobel economic recipe: Help states, add stimulus. National Public Radio Interview on October 31, 2010. https://www.npr.org/templates/story/story.php?storyId=130955806

Eiling, E., & Gerard, B. (2014). Emerging equity market Comovements: Trends and macroeconomic fundamentals*. Review of Finance, 19(4), 1543-1585. https://doi.org/10.1093/rof/rfu036

Fama, E. F., & French, K. R. (1992). The cross-section of expected stock returns. The Journal of Finance, 47(2), 427-465. https://doi.org/10.1111/j.1540-6261.1992.tb04398.x

First Sentier Investors. (2013). Strategic Asset Allocation.

First Sentier Investors. (2014). Dynamic Asset Allocation.

First Sentier Investors. (2021). Regimes, Turbulence and Absorption – A new way of looking at risk.

Forbes, K., & Rigobon, R. (1999). No contagion, only interdependence: Measuring stock market Co-movements. https://doi.org/10.3386/w7267

Guidolin, M., & Timmermann, A. (2005). Asset allocation under multivariate regime switching. https://doi.org/10.20955/wp.2005.002

Jegadeesh, N. (1990). Evidence of predictable behaviour of security returns. The Journal of Finance, 45(3), 881-898. https://doi.org/10.1111/j.1540-6261.1990.tb05110.x

Jurado, K., Ludvigson, S. C., & Ng, S. (2015). Measuring uncertainty. American Economic Review, 105(3), 1177-1216. https://doi.org/10.1257/aer.20131193

Kritzman, M., & Li, Y. (2010). Skulls, financial turbulence, and risk management. Financial Analysts Journal, 66(5), 30-41. https://doi.org/10.2469/faj.v66.n5.3

Kritzman, M., Li, Y., Page, S., & Rigobon, R. (2010). Principal components as a measure of systemic risk. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.1633027

Mahalanobis, P.C. (1927). Analysis of Race-Mixture in Bengal, Journal of the Asiatic Society of Bengal, vol. 23: 301–333.

Mahalanobis, P.C. (1936). On the Generalised Distance in Statistics, Proceedings of the National Institute of Sciences of India, vol. 2, no. 1:49–55.

Mandelbrot, B. (1963). The variation of certain speculative prices. The Journal of Business, 36(4), 394. https://doi.org/10.1086/294632

Markowitz, H. (1952). Portfolio selection. The Journal of Finance, 7(1), 77. https://doi.org/10.2307/2975974

Meinen, P., & Roehe, O. (2017). On measuring uncertainty and its impact on investment: Cross-country evidence from the euro area. European Economic Review, 92, 161- 179. https://doi.org/10.1016/j.euroecorev.2016.12.002

Nalewaik, J. (2015). Regime-switching models for estimating inflation uncertainty. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.2676273

Pukthuanthong, K., & Roll, R. (2009). Global market integration: An alternative measure and its application. Journal of Financial Economics, 94(2), 214- 232. https://doi.org/10.1016/j.jfineco.2008.12.004

Rosenberg, B., Reid, K., & Lanstein, R. (1985). Persuasive evidence of market inefficiency. The Journal of Portfolio Management, 11(3), 9-16. https://doi.org/10.3905/jpm.1985.409007

Rouwenhorst, K. G. (1997). International momentum strategies. SSRN Electronic Journal. https://doi.org/10.2139/ssrn.4407

Sornette, D. (2002). Predictability of catastrophic events: Material rupture, earthquakes, turbulence, financial crashes, and human birth. Proceedings of the National Academy of Sciences, 99(Supplement 1), 2522-2529. https://doi.org/10.1073/pnas.022581999

Stock, J., & Watson, M. (2012). Disentangling the channels of the 2007-2009 recession. https://doi.org/10.3386/w18094

Zhang, J., Lai, Y., & Lin, J. (2017). The day-of-the-Week effects of stock markets in different countries. Finance Research Letters, 20, 47-62. https://doi.org/10.1016/j.frl.2016.09.006