Tactical asset allocation using the Kalman filter

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Abstract

Tactical asset allocation (TAA) is a dynamic investment strategy which seeks actively to adjust fund allocation to a variety of asset classes by systematically exploiting inefficiencies and temporary imbalances in equilibrium values. This approach contrasts with strategic asset allocation (SAA) in which a long-term investment view target allocation is established using a combination of target return and risk tolerance. Asset returns are forecasted using the Capital Asset Pricing Model (CAPM), complemented with results obtained from the Kalman filter. Performance of TAA and SAA approaches are compared using several diagnostic metrics. The TAA approach outperforms its SAA counterpart for most of these metrics for the period under consideration, showing some potential benefits of using this approach.

KEYWORDS: Asset allocation; CAPM; Kalman filter; market timing; strategic asset allocation; tactical asset allocation

JEL CLASSIFICATION: C22; G11; G17

1. Introduction

TAA is a dynamic strategy which seeks actively to adjust the allocation of funds to a variety of asset classes (Shtekman & Stockton, 2010). It aims to systematically exploit inefficiencies and/or temporary imbalances in equilibrium values among different asset classes. The debate around the use of TAA to complement SAA techniques has been an ongoing discussion for numerous years. TAA has the following objectives:

- increasing portfolio returns
- adapting to market conditions
- providing diversification (i.e., reducing portfolio risk).

There exists extensive literature on the use of various tools and methodologies which have been incorporated into portfolio strategies to deliver the best possible outcome for investors (Ammann & Zimmermann, 2001; Blitz & van Vliet, 2008; Clewell et al., 2017; Dahlquist & Harvey, 2005; Nystrup et al., 2016). These have been tried and tested, but the jury is still out regarding their effectiveness to produce meaningful returns for tactically managed portfolios. This is especially true for multi-asset funds which aim to achieve an even greater level of diversification by investing in largely uncorrelated assets and hence income streams (Perold, 2004). The decisions that must be made in any active management strategy are based on a variety of indicators, some of which function on a standalone basis while others are used in an integrated system – see, for example, Flint and Maré (2019). These indicators are used to identify a changing economic environment where market inefficiencies possibly exist and to exploit these inefficiencies to best serve an investor's portfolio.

The issue however is that these financial indicators must be forecasted as accurately as possible to prevent making decisions which could be to the detriment of an investment portfolio. Forecasting of financial data has proven to be a significant challenge to market practitioners because financial data are often beset with noise (Thomson & van Vuuren, 2018). They are not only tainted with noise, but incorrect data entries, missing data and spurious outliers are also common in financial data which renders the forecasting thereof a complex procedure. There therefore exists the need for a dynamic approach to financial forecasting which produces much more recent and hence relevant estimations of the nature of markets. The Kalman filter, which has its roots in engineering (Kalman, 1960), has been proposed as an example of such a dynamic approach and attempts to improve on the performance of other methods of financial time series estimation such as simple linear regression and exponentially weighted moving averages (Arnold et al., 2008). The Kalman filter is not completely new to the financial world and there already exists many examples of its application in financial engineering and the broader quantitative finance landscape (Burmeister et al., 1986; Faff et al., 2000; Schwartz, 1997). In this research, the Kalman filter algorithm is used to estimate the time-varying, unobservable variables of the popular Capital Asset Pricing Model (CAPM).

The CAPM was introduced by Sharpe (1964) and follows directly from portfolio mean-variance analysis (Markowitz, 1952), the foundation of passive portfolio construction. It has become one of the most well-known asset pricing models in recent history and is used in various ways, such as estimating the cost of capital for firms and, more relevant to this study, evaluating the performance of managed portfolios (Perold, 2004). In his work, Sharpe (1964) showed that the excess returns of an asset or a portfolio of assets were a linear function of the excess market returns, where the returns of the overall market were represented by a market-capitalised equity index (Sharpe, 1964). The CAPM falls into a broad category of single-factor models (SFM) used in the investment industry, although multi-factor models have become increasingly popular (Fama & French, 1993; Fama & French, 2015).

The use of the Kalman filter in the CAPM framework assists in the forecasting of asset returns. Based on these forecasts, a rules-based TAA framework is developed and implemented with the intention of achieving one of the underpinning objectives of tactically weighted multi-asset portfolios in particular, which is increasing portfolio returns.

The rest of this article is set out as follows: A literature review of existing TAA strategies, using a range of indicators which can be categorised into different groups, follows in Section 2. Section 3 describes the asset classes considered in this article and the selected indices which will serve as proxies for these assets' performance. The way price data were obtained and converted into returns data is also discussed in this section, along with the methodology of using the Kalman filter to estimate asset returns and consequently constructing investment portfolios. Section 4 presents the main results, followed by a discussion of these results in the context of various investment performance metrics. Section 5 provides recommendations and concludes.

2. Literature review

SAA specifies target weights to different asset classes in a portfolio based on a long-term view of the returns and risks of these asset classes and the relationship that exists between them, guided by a variety of capital market assumptions. The objective of SAA mainly revolves around meeting the long-term needs of client(s). Portfolio managers and asset allocators who incorporate TAA in their investment strategies on the other hand seek to gain from short-term market movements and temporary changes in economic conditions thereby potentially adding value to the underlying SAA policy from either a return or risk basis or both (risk-adjusted returns) through successful market-timing. There exists a plethora of literature on TAA drivers and the different tools which have been used in the past and are still being developed today to adjust weight allocations to different asset classes within in a portfolio in the most effective and beneficial manner. There are three main categories of TAA drivers: valuation-based methods, macroeconomic scenarios, and more technical/quantitative analyses. These categories are discussed below, following a similar structure to Flint and Maré (2019).

Valuation-based methods have in the past attempted to exploit various market regimes and identify possible changes in market regimes to time the market (Flint & Maré, 2019). This method is based on the underlying principle of value investing whereby investors aim to buy into markets that are cheap and exit positions or avoid markets altogether that are deemed expensive. The market is described as cheap when data suggest it is undervalued relative to historical norms and expensive when overvalued relative to historical norms.

There are various indicators which are commonly used within value investing, some being used in combination with one another or that are layered in different filtering levels. The most popular of these indicators include the price-to-earnings or PE ratio, the price-to-book ratio, and the price/earnings-to-growth ratio. An indicator which has recently received considerable attention from market practitioners is the cyclically adjusted price-earnings ratio or CAPE (Campbell & Shiller, 1988). The CAPE ratio is calculated using the current stock price of a company and dividing it by its long-term average earnings, adjusted for inflation. Importantly, this ratio assesses financial performance over a specified period, while isolating the impact of economic cycles. Given that it explicitly accounts for economic cycles, it allows analysts to evaluate a company's broader profitability over time by smoothing out any cyclical effects.

As is evident in this definition of the CAPE ratio, it allows portfolio managers to make decisions regarding the equity portion of their investment portfolios by considering the overall financial stability of individual stocks, but also that of different sectors and industries. Using the information contained in this ratio, portfolio managers can decide to limit their exposure to the equity market, or certain portions thereof, if they foresee a drop in returns or perhaps increased volatility levels and instead move some of the funds to other asset classes such as cash. The changes to weights allocated to different asset classes based on the outlook one may have of certain segments of the market encapsulates the main motivation behind TAA (Shtekman & Stockton, 2010).

Another method of establishing a changing market environment, which will ultimately also affect the nature of returns of various asset classes, uses *macroeconomic indicators*. Clewell et al. (2017) showed that the 'sensitivities of size-sorted stock portfolios to rates, industrial production, inflation, credit spreads, and consumption explain a significant portion of their relative performance over time'. As some economic indicators are often closely linked to asset classes, it is important to remember that SAA is the single biggest factor responsible for variation in portfolio performance.

Fama and French (1989) also conducted a study into the effect of macroeconomic variables in the returns of securities. The first factor considered was the so-called default spread, measured as the difference in yield between a market portfolio of corporate bonds and the risk-free rate. The second factor was the dividend yield, commonly used to forecast stock returns. The final factor was the term spread which indicates the spread in yield earned on the one-month US treasury bill rate and the risk-free rate (i.e., the yield earned on AAA sovereign securities). Fama and French (1989) concluded that the default spread, a business-conditions variable, is high during periods of persistently poor performance by business evident, for example, during periods such as the Great Depression. The default spread is low on the other hand in the presence of strong economic conditions. The dividend yield was found to be correlated to the default spread and moves in a similar fashion relative to long-term business conditions. Lastly, the term spread is related to shorter-term business cycles, being high near troughs and low during peaks.

There exists even more evidence on the effect of macroeconomic factors on security returns and how this ultimately influences decision-making regarding asset allocation and the tactical tilting of weights across various asset classes. Many of these factors are listed in Clewell et al. (2017), which suggests that these factors are indeed priced into markets, albeit to different extents.Footnote[1]

The third of the three broad categories of drivers of market timing, i.e., *technical or quantitative*, is in certain ways much simpler in its application, yet extremely useful in terms of the benefits it offers to portfolio managers. As mentioned in Flint and Maré (2019), these types of technical indicators have recently become common practice in many systematic trend-following trading strategies to scale portfolio exposures tactically to a range of asset classes. The indicators, even though it is easier to understand and implement, can also vary in terms of its complexity relative to other indicators in this same category.

One such system proposed by Faber (2017) uses one of the most well-known measures of trend, the 200-day simple moving average (SMA), together with one simple trading rule. The rule states that when the equity index in question is trading above its 200-day SMA, then the exposure to equities will remain unchanged and when the index is trading below its 200-day SMA, then this exposure will decrease, with the excess funds being allocated to cash or cash-like securities. This simple system was implemented, at first only considering two asset classes, equities and cash, and produced a portfolio which produced equity-like returns at levels of volatility often associated with bonds. These results were produced over an extended time-period and included many important historical events and encompassed multiple business cycles, essential for meaningful evaluation of TAA strategies.

The updated system weighted all the new asset classes equally, i.e., 20% allocation across each of the five asset classes in question (equities, bonds, cash, real estate, commodities). Each of the asset classes was considered independently, with exposures remaining at the stated 20% level unless it was trading at levels below its own 200-day SMA, in which case the 20% allocation was moved to cash once again. This method, termed the quantitative tactical asset allocation (QTAA) portfolio was compared to a global tactical asset allocation (GTAA) portfolio which simply represented a buy-and-hold portfolio using an equal weighting scheme across the same asset classes. The results for both the in-sample and out-of-sample periods showed the same trends, with the QTAA portfolio providing higher returns and with lower levels of risk.

Other literature shows how another quantitative indicator, the VIX (CBOE Volatility Index), is used (Copeland & Copeland, 1999; Nystrup et al., 2016; Vorlow, 2017). The VIX was created to measure expected volatility in the equity market, specifically the volatility in the US equity market and is often referred to as the 'fear index'. It is based on the prices of options contracts written on the S&P500 index and is calculated aggregating weighted asset prices of these options, both put and call options, over a range of strike prices.

When there exist elevated levels of uncertainty in the equities market, then the amount investors are willing to pay to purchase options contracts to hedge their positions also increases. The increase in the premiums for options is reflected in an increase in the VIX. Copeland and Copeland (1999) show how this indicator is statistically significant and how on days following increases in the VIX, 'portfolios of large-capitalisation stocks outperform portfolios of small-capitalisation stocks'. During this period, value-based portfolios also outperform growth-based portfolios. This point is interesting given the current speculation around the effectiveness of value-based strategies which in recent years have underperformed their growth-based counterparts. On the days following a decrease in the VIX the opposite occurs. This once again gives portfolio managers a sense of the performance of markets in the short term, presenting them with an opportunity to add value to their portfolios if executed accurately.

Probabilistic momentum and implied volatility, which when used in combination can produce a four-state market classification (Flint & Maré, 2019), is another example among the literature on the use of quantitative indicators in TAA.

3. Data and methodology

3.1 Data

For this study, the available assets for SAA have been limited to equities, bonds, cash, real estate and commodities. These assets inherently also formed part of the TAA strategy's universe of investable assets, ensuring that both the SAA and TAA strategies had the same set of asset classes with which to construct portfolios.

shows the different asset classes and the indices used to represent each asset class's overall performance.

Table 1. Asset classes and their respective indices.

Asset class	Index
Equities	MSCI ACWI
Bonds	FTSE WGBI
Cash	Three-month treasury bills
Real Estate	S&P Global REITS
Commodities	S&P GSCI

Monthly price data were gathered for all the indices used for this research. As many data as possible were collected across the different asset classes. The earliest date for which there were data across all the indices was selected as the starting point for this investigation. This date is set at 1 Jan-11. The final date for which data were available at the time this study was conducted was 31 May-20. This end date forms a critical part of this study given the market downturn experienced during the early months of 2020 at the height of the coronavirus pandemic. Special attention will be paid to this period to evaluate the performance of the TAA approach compared to some of the other investment strategies employed during normal market conditions.

Price data sourced for the various asset classes' indices were then used to determine the logarithmic monthly returns ($\boldsymbol{R_t}$) using:

$\boldsymbol{R_t} = \ln\left(\frac{\boldsymbol{P_{t+1}}}{\boldsymbol{P_t}}\right)$ where $\boldsymbol{P_t}$ are prices observed at time $\boldsymbol{t}$. These returns are used to compute excess asset/portfolio returns, the observable variable in the Kalman filter algorithm which in turn is used to estimate time-varying, unobservable variables, $\boldsymbol{\alpha}$ and β

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3.2. Methodology

3.2.1. Using the Kalman filter and the CAPM to forecast asset returns

The development of the CAPM in Sharpe (1964) was largely based on the framework defined by Markowitz (1952) and it showed that the excess returns of an asset or a portfolio of assets were a linear function of the excess market returns represented by a market-capitalised index such as the S&P500 index or the MSCI ACWI. The CAPM is:

$$R_p - R_f = \alpha + \beta(R_m - R_f) + \epsilon \qquad (1)$$

where R_p is the portfolio return, R_f the risk-free rate of return, α is the excess return, β is gearing of excess market returns (R_m) over the risk-free rate to excess portfolio returns and ϵ captures error (or noise) terms. In the context of the Kalman filter, (1) is the measurement equation. For ease of exposition, the subscripts in (1) will be written as superscripts allowing for the use of subscripts to indicate the specific point in time. Furthermore, the excess returns, both that of the portfolio as well as the market will be written as single variables, $R_p{-}R_f$ will be written as R_p and $R_m{-}R_f$ will be written as R^m.To this end (1) now takes the form:

$$R_t^p = \alpha_t + \beta_t R_t^m + \epsilon_t \qquad (2).$$

at time t and the noise term $\epsilon_t \sim N(0, \sigma_t^2)$.

Since the transition equation allows for the development of variables over time, an assumption needs to be made in terms of the process which drives this development, which would then ultimately also determine the form of the transition equation. There are various options to choose from when deciding which underlying stochastic process would be most suitable for the time-varying unobservable variables α

and β. The options consist of processes such as autoregressive models, mean-reverting models, random walk processes, different distributional assumptions etc. Faff et al. (2000) for example examined the ability of alternative models in capturing the time-variation of systemic risk or β. For their implementation of the Kalman filter three different stochastic processes were tested namely, a random walk, a first order autoregressive process with a constant mean, and a random coefficient around a constant mean. The results suggested that the 'Kalman filter algorithm, and in particular with the random walk parameterisation, consistently performs better than the simple market model β' (Faff et al., 2000). Therefore, the random walk process is also incorporated in this Kalman filter implementation for both time-varying parameters in question.

According to the random walk process, current market exposure is assumed to be a normally distributed random variable with a mean equal to the mean of the previous period's exposure and with system noises also assumed to be normally distributed and uncorrelated (Thomson & van Vuuren, 2018). State variables $x_t \in R^2$ are time-varying coefficients:

$x_t = \begin{bmatrix} \alpha_t \\ \beta_t \end{bmatrix}$ at time t. Given the assumption that these variables develop according to a random walk process, the transition equation is written, in matrix form, as

$$\begin{bmatrix} \alpha_{t+1} \\ \beta_{t+1} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} \alpha_t \\ \beta_t \end{bmatrix} + \begin{bmatrix} \gamma \\ \delta \end{bmatrix} \tag{3}$$

where

$$\begin{bmatrix} \gamma \\ \delta \end{bmatrix} \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{bmatrix} \sigma_\gamma^2 & 0 \\ 0 & \sigma_\delta^2 \end{bmatrix} \right)$$

Given that (3) is written in matrix form, the same will be done for (2). Therefore, the measurement equation can be re-written as:

$$R_t^p = [1 \quad R_t^m] \begin{bmatrix} \alpha_t \\ \beta_t \end{bmatrix} + \epsilon_t \tag{4}$$

There are, however, some parameters, which are not estimated during the Kalman filter process, but rather which feed into the algorithm. Maximum likelihood estimation is used to determine the remaining unknown variables, in this instance σ_γ^2 and σ_β^2. The use of maximum likelihood estimation in conjunction with the Kalman filter algorithm is known as the Expectation Maximisation algorithm (Brockwell et al., 2002).

If further it is assumed that the risk-free rate and market return are both Martingales, and that $\epsilon_t \sim N(0, \sigma_t^2)$, then from (1), and by decomposing excess returns into their individual component once again, portfolio returns at *t*+1 are:

$$E\left[R_{t+1}^p\right] = E\left[R_{t+1}^f + \alpha_{t+1} + \beta_{t+1}\left(R_{t+1}^m - R_{t+1}^f\right) + \epsilon_{t+1}\right] = R_t^f + \alpha_t + \beta_t\left(R_t^m - R_t^f\right)$$
(5)

where α_t and β_t represents adjusted predictions considering observed values at *t* within the Kalman filter setup.

3.2.2. Portfolio construction based on forecasted asset returns

According to Faber (2017), the following criteria are necessary to implement a purely quantitative method to asset allocation:

1. it must have simple, purely mechanical logic,
2. the same model and parameters must be used across all the different asset classes being invested in, and
3. it must be a price-based model.

These requirements provided the guiding principles in the formulation of the proposed alternative quantitative approach to TAA in this study. The strategic weights (i.e., the SAA) which are set first on an annual basis, at the start of each new year, serve as the foundation on which the TAA framework will attempt to construct portfolios which aim to benefit from market-timing. When the SAA weights are set, they remain unchanged until the annual rebalancing of the portfolio. The SAA weights are set according to a chosen weighting technique (minimum variance, maximum diversification,Footnote[2] or maximum Sharpe ratio). Then, in terms of periods, an investor or portfolio manager acting on behalf of the investor, has the freedom to choose a lookback period and a desired evaluation period, both of which are in months.

The lookback period will determine how many months' worth of return data will be taken into consideration when setting the SAA weights of the portfolio. The evaluation period is the window over which the SAA and TAA frameworks will be compared. The window should ideally be less than 12 months to allow for the possible rebalancing of the SAA portfolio. If the evaluation period is required to be longer than 12 months then it is suggested that the same process is followed over each year, rebalancing at the start of each new 12-month period.

At this stage, the investor or portfolio manager has selected a lookback period, a SAA weighting technique, and an evaluation period. The other two parameters that can be set are the maximum allocation to cash or cash-like securities and the portion of funds, expressed as a percentage of the weight allocated in equities, which is allowed to be invested in other asset classes. The maximum cash allocation for SAA has a strong bearing on the weights allocated towards other asset classes, particularly equities, and can determine whether the fund sits at the high or low equity spectrum of multi-asset funds. In simpler terms, the lower the allocation in cash, the more funds are made available for investment in the other asset classes which form part of the opportunity set of investable assets.

The proposed alternative quantitative TAA strategy, which allows for deviations from the SAA weighting based on forecasted asset class returns then allocates funds between equities, bonds, cash, real estate, and commodities using the min-max framework, explained below, with the SAA weights serving as the starting point for these portfolio tilts.

To clearly set out the decision-making process for the TAA strategy, different scenarios will be considered along with the corresponding actions that will be taken depending on what the following month's estimated asset returns look like. This TAA framework only explores those asset classes which offer the minimum and maximum estimated returns as forecasted by the CAPM which incorporates the Kalman filter estimates of α and β. To this extent, various scenarios are highlighted below, followed by the action taken according to this TAA framework.

- Equities estimated to offer minimum return, r , and $r>0$

  In this instance the SAA weight invested in equities is reduced and funds are allocated to either cash, real estate, or commodities, depending on which is estimated to offer the maximum return, also positive in this instance, over the next month.

- Equities estimated to offer minimum r and $r<0$, the maximum estimated $r>0$

Here the SAA weight invested in equities is again reduced and funds are allocated to either cash, real estate or commodities, depending on which is estimated to offer the maximum (positive) return over the next month.

- Equities estimated to offer minimum *r* and this return along with the maximum estimated return are both <0

  Here the SAA weight invested in equities is once again reduced and funds are allocated to either cash, real estate, or commodities, depending on which is estimated to offer the maximum return over the next month. This could entail a long position being taken in an asset class which is also estimated to offer negative returns to decrease the effect of the most negative returns offered by the equity asset class.

- Real estate/commodities are estimated to produce the minimum *r*, but *r*>0

  If the SAA weight is negative, i.e., a short position, this position will remain the same to prevent hurting portfolio returns as a result of changes to this position. If the SAA weight is positive, the weight will be reduced and excess weight will be allocated to the asset class which offers the best possible return, also positive, over the next month.

- Real estate or commodities is estimated to produce the minimum *r* (*r*<0) and the maximum estimated *r* across remaining assets is >0

  A short position is taken, thus resulting in a positive return, and a long position is taken in the asset which is estimated to offer the highest returns. If this asset class is either the equity asset class or cash, then its existing SAA weight will simply be increased.

- Real estate or commodities is estimated to produce the minimum ***r*** and both this return and the estimated maximum *r*<0

  SAA weights are kept the same to avoid taking a potential long position for the upcoming month in an asset class which is estimated to produce a negative return.

- Cash is estimated to produce the minimum *r*

  Given how reluctant portfolio managers of multi-asset funds are to reduce their holding in cash, especially during extremely volatile market conditions, the SAA weights, which are already dependent on the maximum cash allocation parameter, will under no circumstances be lowered. It can be increased as was shown in the scenarios above.

The overarching aim of this approach is to increase portfolio returns as mentioned but does not explicitly incorporate constraints or targets in terms of any portfolio risk metrics with this TAA overlay. One could argue that, as we also seek to improve returns when forecasted returns are negative by increasing the weight to an asset class which is forecasted to deliver the least negative return, that portfolio drawdown, one such measure of risk, is indirectly considered. However, this is not the main focus.

4. Results and discussion

This section shows the results obtained by applying the TAA approach. It first focuses on the main metrics used to evaluate the performance of different portfolio investments and the risk associated with these investments. In this section, medium equity (i.e., 40%≤ exposure to equities ≤60% of SAA annual weights) will also be mentioned throughout. One could ultimately choose the exposure to equities one desires, but for the purpose of this section it was chosen to limit the exposure to equities to no more than 60% of the total portfolio and no less than 40% in terms of SAA weights set on an annual basis. This was done to replicate a real-life example where fund managers could be mandated to keep the average exposure to equities within certain thresholds in terms of SAA.

Reference is also made to the 'market', which simply represents a 100% investment to the equity index chosen for this research, the MSCI ACWI.

shows the main performance metrics (average annual return, average annual volatility, Sharpe ratio and maximum drawdown) for the three SAA weighting techniques. These metrics are measured from January 2011 to the end of May 2020.

Table 2. Descriptive statistics for market, SAA and TAA portfolios from 1-Jan-11 to 31-May-20.

	Weighting portfolio		
Minimum variance	Market	SAA Medium Equity	TAA Medium Equity
Annual return	5.64%	3.62%	6.29%
Annual volatility	13.57%	6.94%	7.27%
Sharpe ratio	0.37	0.43	0.78
Maximum drawdown	−22.69%	−11.31%	−7.59%
Maximum diversification			
Annual return	5.64%	1.99%	4.47%
Annual volatility	13.57%	9.48%	8.33%
Sharpe ratio	0.37	0.15	0.46
Maximum drawdown	−22.69%	−17.55%	−13.79%
Maximum Sharpe ratio			
Annual return	5.64%	6.80%	12.34%
Annual volatility	13.57%	8.75%	11.62%
Sharpe ratio	0.37	0.71	1.01
Maximum drawdown	−22.69%	−10.74%	−10.30%

For all three SAA weighting techniques, the addition of the TAA framework saw an improvement in the average annual return achieved by the portfolios. For the minimum variance weighting technique, the average annual return was also increased from being below that offered by the market to exceeding market returns. This was done without a significant increase in the risk faced by the portfolio, measured as the average annual volatility of portfolio returns. For the maximum diversification ratio weighting technique, the TAA portfolio showed decreased levels of risk when compared to its SAA counterpart. For the maximum Sharpe ratio portfolio there was a noticeable increase in the risk associated with the TAA portfolio, despite this technique delivering on its objective in terms of returns, along with a corresponding increase in the Sharpe ratio. Given the assembly of the Sharpe ratio, it is evident that the TAA's return element must have outperformed the risk element.

In terms of the Sharpe ratio, and as would be evident from the preceding paragraph, the TAA portfolios all saw an improvement during the time under observation. The Sharpe ratio for the maximum diversification TAA portfolio, for example, more than doubled the value achieved by the SAA portfolio. The maximum drawdowns faced by these portfolios were also less than its SAA counterparts, albeit to varying magnitudes across the three weighting techniques. This is promising for investors who place a great deal of emphasis on capital preservation, especially during negative market conditions.

A different perspective would be to look at the total return, shown as the cumulative value of a portfolio over the period in question, of the various SAA portfolios as well as its associated TAA portfolios. The final values of the portfolios were measured at the end of May 2020 and is shown in Figures 1, 2 and 3. The cumulative return of the market is also shown.

Figures

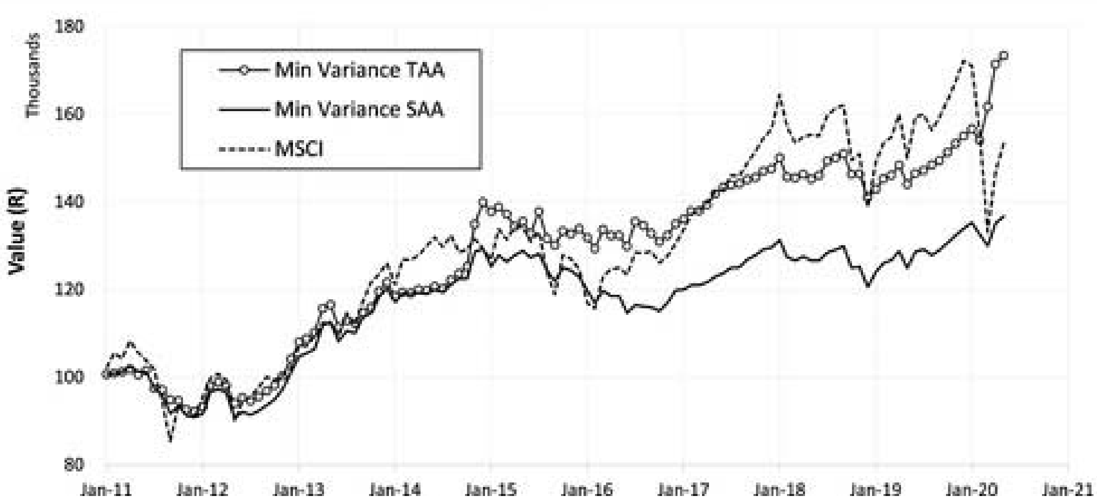

Figure 1. Cumulative performance of minimum variance SAA and TAA portfolios using data spanning January 2011 to May 2020. (Source: Own calculations.)

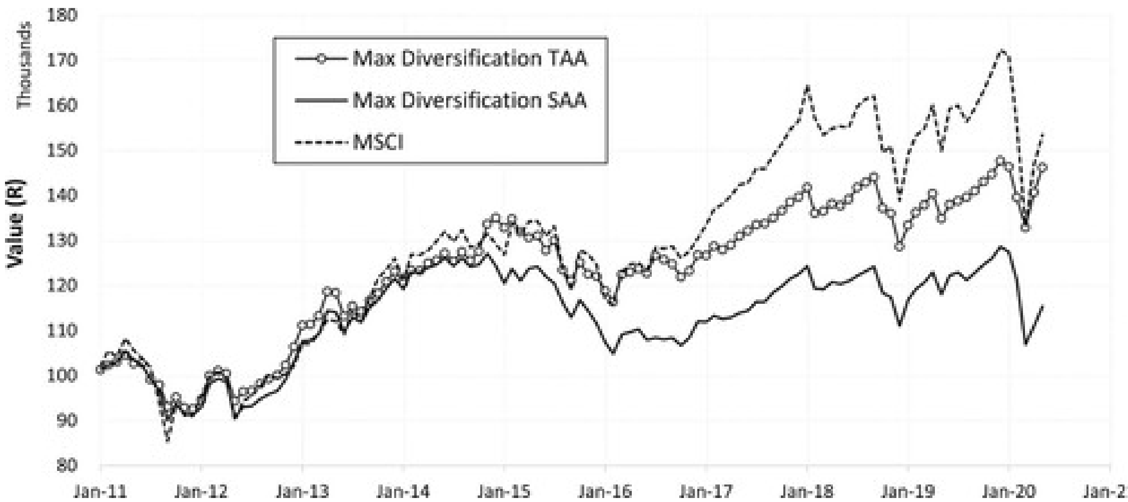

Figure 2. Cumulative performance of maximum diversification SAA and TAA portfolios using data spanning January 2011 to May 2020. (Source: Own calculations.)

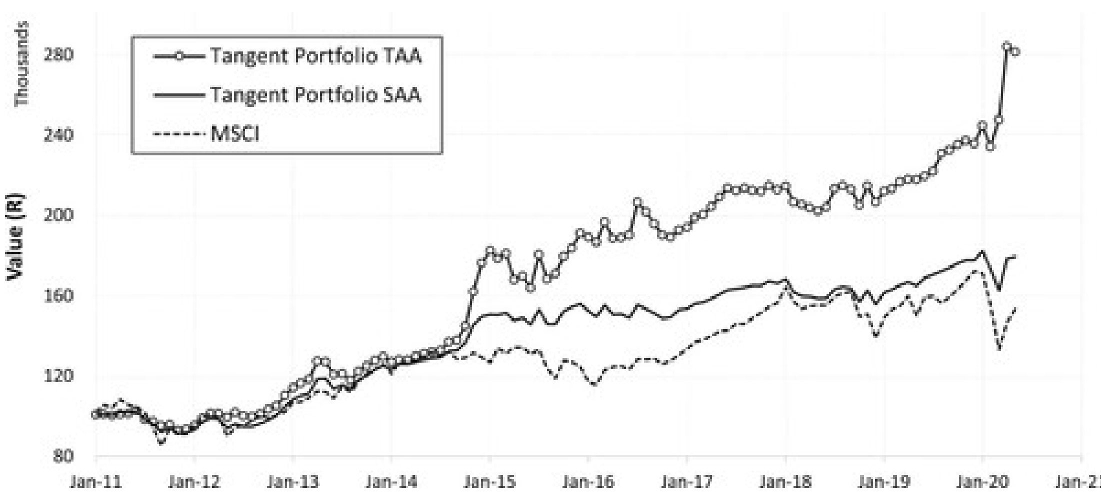

Figure 3. Cumulative performance of maximum Sharpe ratio SAA and TAA portfolios using data spanning January 2011 to May 2020. (Source: Own calculations.)

The results show that each of the TAA portfolios produced a higher portfolio value than the associated SAA portfolio at the end of May 2020. The significantly higher portfolio value came at some price however in the case of the maximum Sharpe ratio portfolio (Tangent portfolio) in terms of the volatility of returns. This is illustrated in Figure 4 which shows the exponentially weighted moving average (EWMA) volatility of the TAA maximum Sharpe ratio returns relative to its SAA counterpart.

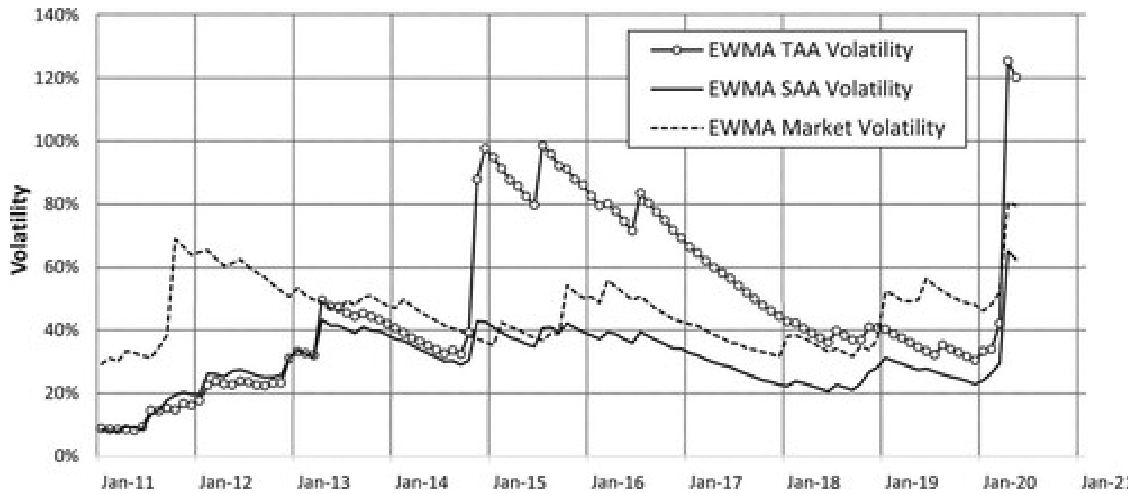

Figure 4. EWMA volatilities of maximum Sharpe ratio SAA and TAA portfolios. (Source: Own calculations.)

The overall risk tolerance of the investor would ultimately determine whether such a TAA strategy would be acceptable. This highlights perhaps one of the shortcomings of the proposed TAA framework, as it is evident in this instance, that it does not take into consideration excess risk the decisions regarding portfolio tilts imposes on the portfolio.

Figures 5–7 show the evolution of the (relative) annualised tracking error (TE) and information ratio (IR) of the respective TAA portfolios over the specified time. Figures 5, 6 and 7 also include shaded areas which represent 'good' IRs (Grinold & Kahn, 2000) using SAA portfolios as benchmark portfolios.

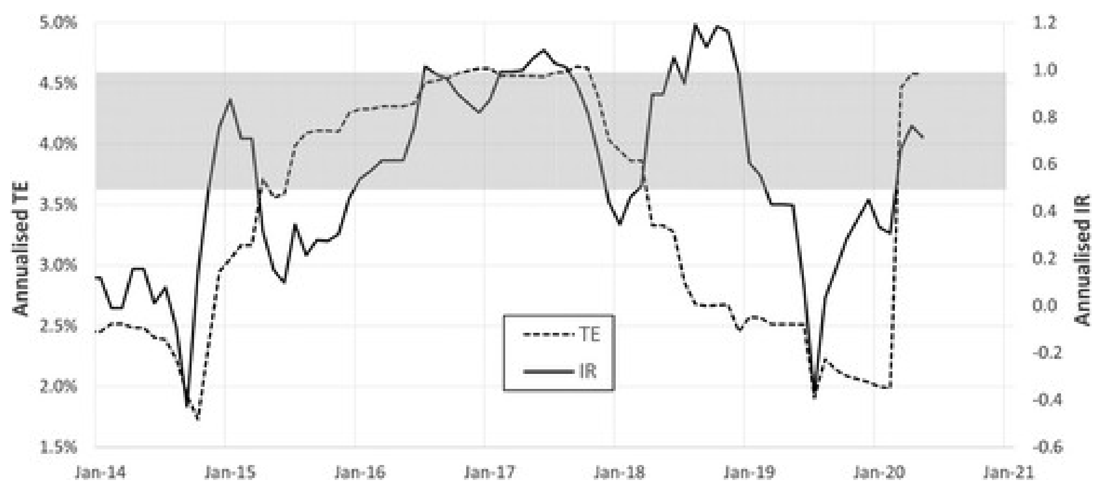

Figure 5. Annualised TE and IR for minimum variance TAA portfolio. The shaded area indicates the region where the 0.5≤*IR*≤1.0, i.e., indicative of outperformance. (Source: Own calculations.)

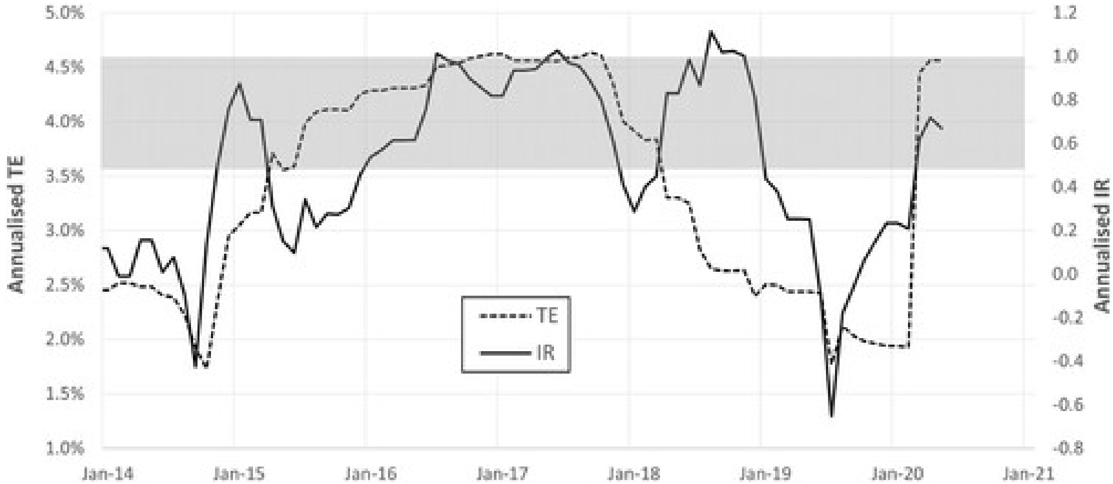

Figure 6. Annualised TE and IR for maximum diversification TAA portfolio. The shaded area indicates the region where the 0.5≤*IR*≤1.0, i.e., indicative of outperformance. (Source: Own calculations.)

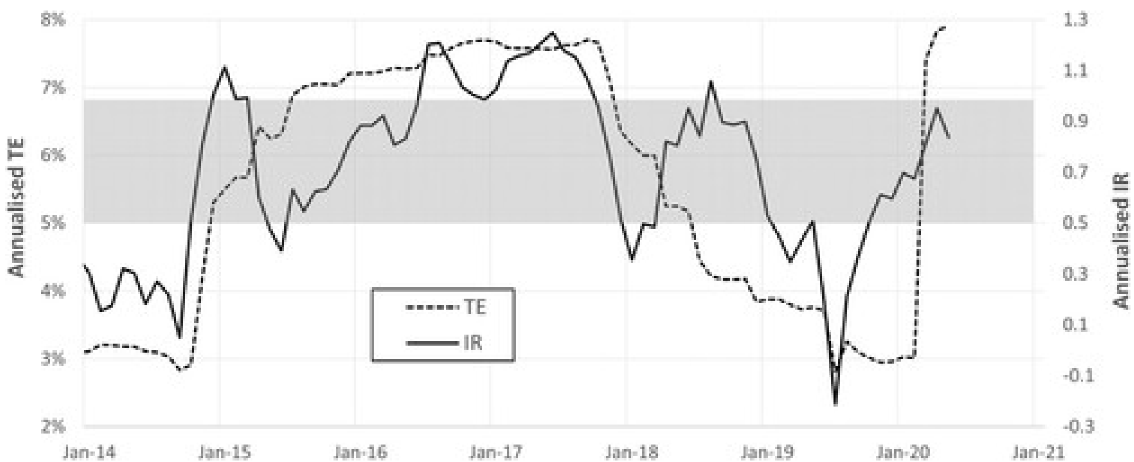

Figure 7. Annualised TE and IR for maximum Sharpe ratio TAA portfolio. The shaded area indicates the region where the 0.5≤*IR*≤1.0, i.e., indicative of outperformance. (Source: Own calculations.)

To calculate TE and IR, 36 months of return data were used and thus these values are shown from January 2014, where enough data had been observed. The results obtained are shown for each of the SAA weighting techniques proposed for this study.

For the TE from 2014 onward, using SAA portfolios as benchmark portfolios, both the minimum variance and maximum diversification TAA portfolios stay within 1%–5%. For the minimum variance TAA portfolio in particular, the TE remains below 4% majority of the time. The maximum Sharpe ratio TAA portfolio shows the highest levels of TE, meaning greater dispersion of excess returns around the mean excess return delivered by the portfolio relative to the SAA portfolio. The higher TE observed for the maximum Sharpe ratio TAA portfolio could be attributable to the lack of constraints regarding the size of the tactical deviations from the SAA benchmark weights, commonly referred to as 'tactical ranges'. With the other two weighting techniques, the allocation towards equities is frequently less than what would be observed with the maximum Sharpe ratio portfolio, and since the size of portfolio tilts are dependent on the portion of the SAA portfolio allocated towards equities, tactical deviations from SAA weights are less extreme.

Lastly, for the given period, all three TAA portfolios delivered IRs which were predominantly positive, indicating the ability of the portfolios to produce excess returns over benchmark portfolios when taking into consideration 36 months' worth of return data. The IRs across all three weighting techniques also entered and remained within the 0.5–1.0 shaded area for large parts, which is indicative of outperformance over a sustained period, a promising result for this TAA framework (Schneider, 2009). There were indeed some periods during which the TAA portfolios underperformed their SAA counterparts per unit volatility of excess returns, i.e., a negative IR.

Transaction fees were not considered. This would erode some of the positive values of the IR these portfolios managed to achieve.

5. Conclusion and recommendations

An alternative TAA approach was investigated to establish whether it would improve the performance of various SAA investment portfolios. This approach is quantitative in nature and uses estimations of α and β parameters as they appear in the CAPM to forecast asset returns. These estimations are produced using the Kalman filter, a time series estimation algorithm which has seen increasing popularity in quantitative finance. This algorithm aims to produce estimations of unobservable data which are more recent, relative, and thus a much more accurate representation of current market conditions as measured by α and β.

These estimations and subsequent return forecasts were used in the min-max TAA framework. The objective of this TAA approach, which assesses forecasted returns produced by the CAPM using Kalman filter estimates of α and β, and adjusts asset class weights accordingly, was to improve the overall performance and risk characteristics of portfolios which would otherwise employ a strategic and thus more static weighting allocation. These improvements would be because of an effective quantitative market-timing mechanism which allows a portfolio manager to enter and exit certain market segments in such a way that it could exploit inefficiencies and temporary imbalances in equilibrium values.

Changes in the overall behaviour of the TAA portfolios were observed compared to their SAA counterparts as evidenced by comparisons with key industry performance and risk metrics. TAA portfolios showed statistically significant improvement in average annual return, Sharpe ratio and cumulative performance over SAA portfolios comprising 10 years of monthly returns (data available on request). Results varied when considering the average annual volatility in portfolio returns and observing EWMA volatilities over this specific period, as some TAA portfolios increased the amount of volatility in returns and thus risk faced by the portfolio, whereas others limited this risk. The maximum drawdown of the TAA portfolios also showed noticeable improvements, albeit at different levels.

Despite a lack of explicit constraints relating to the behaviour of the TAA portfolios relative to its SAA counterparts, the TE of two of the TAA portfolios never exceeded 4%, whilst still producing average to above average IRs for sustained periods.

Disclosure statement

No potential conflict of interest was reported by the authors.

Notes

1 Macroeconomic factors influence TAA decisions as well as also SAA decisions. The most common methodology for formulating SAA involves the estimation of macroeconomic forecasts and how these drive asset class performance.

2 Maximum diversification here refers to the optimisation approach suggested by Choueifaty and Coignard (2008).

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