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Protected Adaptive Asset Allocation

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A B S T R A C T

Protected Adaptive Asset Allocation (PAAA) is a tactical asset allocation model that targets an optimal risk/returns ratio using both a momentum index to capture the short-run dynamics and cash protection in negative market periods to reduce drawdowns. Empirical evidence shows that PAAA improves upon the performance of alternative models in terms of the risk/return profile when applied to a well-diversified dataset in the long term, based on the results of in/out-of-sample analyses, and when the analysis is restricted to a financial crisis period. For less diversified portfolios, PAAA is equivalent to an Adaptive Asset Allocation that includes a liquidity component.

1. Introduction

The recent financial crisis has led to global economic troubles and has restored the interest of investors in more prudent investment management strategies. Most strategies continue to be based on the Modern Portfolio Theory (MPT, Markowitz (1952)) which aims to reduce investment risks by diversifying asset allocation. A common practice is to select assets based on their historical volatility and returns to optimise the risk/return ratio and then hold them in the long term. This approach ignores the short-term financial market dynamics to which investors are exposed, which generally focus on targets with a limited time horizon. In fact, the optimum portfolio weights are sensitive to return expectations, which are usually difficult to determine. For instance, historical returns are bad predictors of future returns (Ni et al. (2011)) and estimating covariance matrices presents a difficult statistical challenge that requires sophisticated analytical methods (see, for instance, Ledoit and Wolf (2004)).

The main aim of this paper is to exploit the MPT approach to construct an investment model called Protected Adaptive Asset Allocation (PAAA), which targets an optimal risk/return ratio by considering the short-run dynamics. As such, PAAA reduces the negative influence of short-run dynamics on 15 portfolio returns and simultaneously reaches the targets of middle-term investors. PAAA is based on the "momentum" that characterises the trend of financial market prices. The renewed investor risk aversion is the basis of the PAAA model, which extends the Adaptive Asset Allocation model (AAA, Butler et al. (2016)) by introducing a cash protection factor to reduce drawdowns. In practice, PAAA selects the best assets on the basis of a short-term momentum index and weights them in order to fix their contributions to the overall portfolio risk. These asset weights are inversely proportional to their individual volatilities and/or pairwise covariances. Additionally, PAAA considers a fraction of liquidity proportional to the number of

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the best assets with unfavourable momentum as an additional portfolio asset (so-called cash protection).

We tested PAAA on real data and compared it with some benchmarks, including the naïve diversification strategy and AAA. We consider two portfolio datasets characterised by different degrees of diversification. First, we performed a long-term analysis of an in/out-of-sample approach used to dispel possible data-snooping problems. Next, we performed a short-term analysis based on a rolling-period approach to evaluate the performances of different strategies when applied over the typical investor holding period. Finally, we restricted our analysis to the years of the recent financial crisis to test the ability of PAAA in very negative market periods. The results show that PAAA outperforms the balanced portfolio in terms of both risk and return and is the best strategy when the universe is well-diversified. When dealing with a less-diversified universe, PAAA can be considered to be a valid alternative to other approaches, particularly AAA, in the long run. If the investment horizon ranges from three to five years, PAAA is the best performer for any possible level of portfolio diversification.

The remainder of this paper is organised as follows. We present the PAAA model in Section 2. In Section 3, we describe the datasets used for our empirical analysis and present information about the calibration of model parameters and the performances of different PAAA specifications in comparison with AAA. In Section 4, we summarise the results of some robustness checks and focus on an in/out-of-sample experiment, a rolling period experiment and an additional analysis specifically focused on the financial crisis period. In Section 4, we end the paper with some concluding remarks.

2. Protected Adaptive Asset Allocation (PAAA)

2.1. Background

”Momentum is the premier market anomaly. It is nearly universal in its applicability”. In this way (Antonacci, 2012) presents a deeper review of this topic and describes the momentum factor on which we have based the PAAA approach. Since the efforts of Jegadeesh and Titman (1993), several authors have tried to explain this market anomaly that, as Fama and French (2008) observed, “*is left unexplained by the three-factor model of Fama and French (1993) as well as by the CAPM*”. In this framework, Clarke et al. (2006) find a relationship between the systematic component of earnings momentum and price momentum. Clarke et al. (2006) canonized momentum as one of the marketwide determinants of realised portfolio returns in the US equity market. Mao and Wei (2014) explain momentum by analysing cash flow and discount rate news. Hong and Stein (1999), as well as Daniel et al. (1998), base their explanations on under–over-reaction phenomena. Karolyi and Kho (2004) test whether different returns-generating models can explain the profitability of momentum strategies. Lastly, Chiang and Huang (2011) attest to the importance of the momentum factor, which demonstrates the impacts of momentum on the performance forecasts of GARCH option pricing models.

Our approach belongs to the class of momentum-based tactical asset allocation models. It builds on the AAA concept introduced by Butler et al. (2016). AAA is motivated by the consideration that investors often use long-term average asset returns and risks to establish optimal portfolios, but these long-term estimates are subject to large errors in the intermediate term. As small estimation errors can lead to large errors in the portfolios established using MPT, AAA relies on shorter-term rolling estimates of risk, diversification and returns that change through time in response to observed changes in markets and then delivers more resilient portfolios. In this respect, AAA updates portfolios periodically, holding onto the assets expected to have the best performance based on momentum. Then, portfolio weights of the selected assets are computed as those that minimise the expected portfolio volatility. Minimisation involves the previous n-days covariances in case momentum is extended to correlations and volatilities. AAA markedly outperforms the naïve diversification strategy in terms of both risk and return.

Like PAAA, other approaches have been proposed that focus more on investor risk aversion and on the use of a filter based on the absolute momentum rule to improve the maximum drawdown of a portfolio by shifting the asset allocation towards cash in bear market periods (the so-called cash protection). Keller and Keuning (2016) introduced the protective asset allocation (PAA) model that maintains the best assets in terms of momentum and the use of a moving average as a market trend indicator, as well as adding cash protection in bear market periods whose magnitude is proportional to the observed market trend. Similarly, in Keller and Van Putten (2012) and Keller and Butler (2014), the fraction of investment with a momentum performance below a certain threshold is replaced with liquidity.

In the following, we present a model for tactical asset allocation that we call PAAA, which is aimed at providing superior risk/return characteristics by using a momentum index to capture the short-run dynamics. As in the literature (e.g. Keller and Van Putten, 2012 and Keller and Butler, 2014), PAAA focuses on cash protection during market downturn periods. The naïve AAA holds in the portfolio the best assets in terms of momentum without, however, any filter for negative performances. In PAAA, our introduction of cash protection is motivated by the idea of overcoming this limitation, whereby the protection involves replacing assets that are showing unfavourable momentum with liquid assets. In this way, we exclude assets that are likely to yield, according to the momentum, negative future returns. To further improve the risk-minimisation process, PAAA also considers the momentum effect for the volatilities and correlations. The simplicity of its implementation, without ignoring any fundamental principle needed for the optimisation of the risk/return profile, makes PAAA suitable for any investor seeking an optimal portfolio strategy.

2.2. Balanced and volatility-based portfolios

The simplest version of PAAA derives from an equally-weighted balanced portfolio of N assets:

$$\Pi_t = \sum_{i=1}^{N} w_t^i p_t^i \tag{1}$$

where the weight of each asset in the portfolio is expressed as $w_t^i = \frac{1}{p_{t-1}^i N}\ \forall\ i = 1,\ ...,N$. Π_t^{Bal} is the portfolio at time t and p_t^i is the price of the ith asset on the same date.

Since a single asset showing high volatility strongly influences portfolio risk, it is important to rebalance the assets based on their last-period volatilities only, not on their historical volatilities. As the momentum factor can also be applied to portfolio risk, an asset with high volatility in the most recent period(s) will continue to maintain this volatility for a short period in the future. Thus, the short-term volatility allows us to capture short-run variations. In this respect, the volatility-weighted portfolio is defined as follows:

$$\Pi_t^{Vol} = \sum_{i=1}^{N} \frac{(\sigma_t^i)^{-1}}{(\sigma_{\Pi_t})^{-1}} p_t^i \tag{2}$$

Portfolio weights are inversely proportional to recent volatilities and are defined as: $w_t^i = \frac{(\sigma_t^i)^{-1}}{(\sigma_{\Pi_t})^{-1}}$, where σ_t^i and σ_{Π_t} are the standard deviations at time t of the returns of the ith asset and the portfolio Π, respectively.

2.3. Momentum in PAAA

As yet, no expectations about the distribution features of the returns have been determined. To address this issue, we hold in the portfolio only those assets with the most favourable expectations of returns and introduce cash protection. The momentum of each asset is computed and assets whose momentums are lower than a pre-specified threshold are replaced with a liquid asset. Momentum at time t for the ith asset is defined as follows:

$$mom_t^i = \frac{p_t^i}{p_{t-m}^i} \tag{3}$$

where m is the width of the momentum look-back. As such, mom_t^i corresponds to the ratio between the price of the asset i observed at the portfolio update time t and the same price lagged w.r.t. the momentum look-back. If $mom_t^i < 1$, this means that the momentum is unfavourable and the proportion of the portfolio that should be invested in asset i is replaced by cash. In the case of a portfolio selection being solely based on the first top performers in the last period ($NTop_t$ denotes the number of best performers on the rebalancing date t), if $NPos_t$ (the number of assets with $mom_t^i > 1$) is equal to $NTop_t$, the cash protection is not activated.However, if $NPos_t < NTop_t$, cash protection is activated and a liquid asset is included in the portfolio. The updated version of Eq. (1) includes the cash protection as an additional asset, as shown below:

$$\Pi_t^{mom} = w_t^{cash} p_t^{cash} + \Pi_t^{Pos} \tag{4}$$

where:

$$\Pi_t^{Pos} = \textstyle\sum_{i=1}^{NPos_t} w_t^i p_t^i, \qquad \text{with } w_t^i = \left(\frac{1}{NPos_t} \cdot \frac{1}{p_{t-1}^i}\right), \quad \text{for } i = 1, \cdots, NPos_t;$$

$$w_t^{cash} = \left(1 - \frac{NPos_t}{NTop_t}\right) \frac{1}{p_{t-1}^{cash}}.$$

The Π_t^{mom} portfolio is thus composed of the best $NPos_t$ assets in terms of favourable momentum plus the cash fraction ($w_t^{cash} p_t^{cash}$) used as protection. The latter is activated only if ($NTop_t - NPos_t$) > 0, namely: when at least one of the best assets has a unfavourable momentum. In contrast, in the case of $mom_t^i > 1$ for each individual asset i ($i = 1,\ ...,N$), this yields ($NTop_t - NPos_t$) = 0, so no liquidity component is included in the portfolio, i.e., cash protection is not activated.

2.4. Combo of momentum, volatility and correlation

The next step is to combine momentum and volatility to specify a "combined" portfolio (Combo) that includes the best assets in terms of momentum and weights them to set their contributions to the overall portfolio risk as inversely proportional to their individual volatilities. Cash protection is still used in this step. Thus, considering the momentum index introduced in Eq. (3), once again we retain the $NPos_t$ assets for which $mom_t^i > 1$ among the $NTop_t$ assets. If $NTop_t > NPos_t$, cash protection is activated in the same way. Eq. (4) is then modified as follows:

$$\Pi_t^{Combo} = w_t^{cash} p_t^{cash} + \frac{NPos_t}{NTop_t} \Pi_t^{Vol} \tag{5}$$

where:

$$w_t^{cash} = 1 - \frac{NPos_t}{NTop_t};$$

$$\Pi_t^{Vol} = \sum_{i=1}^{NPos_t} w_t^i p_t^i, \qquad \text{with } w_t^i = \frac{(\sigma_t^i)^{-1}}{\left(\sigma_{\Pi_t^{Vol}}\right)^{-1}}, \quad \text{for } i = 1, \cdots, NPos_t.$$

In practice, Π_t^{Vol} is the portfolio component that considers the best assets in terms of momentum, and then weights them so they will contribute proportionally to the volatility of the overall portfolio. Consequently, Π_t^{Combo} indicates a volatility weighted portfolio Π_t^{Vol} with activated cash protection. Since the magnitude of the liquidity component is proportional to the number of assets with unfavourable momentum, the weight of Π_t^{Vol} in Π_t^{Combo} is defined after quantifying the cash protection. The overall weight of Π_t^{Vol} is computed as a ratio between the number of assets with favourable momentum ($NPos_t$) and the number of assets originally held in the portfolio ($NTop_t$). Furthermore, the weight of each individual component of $\Pi_t^{Vol_t}$ is computed as the ratio between the inverse of the standard deviation of the asset i at time t, i.e., σ_t^i, and the inverse of the standard deviation of the portfolio component with no liquidity at time t, namely $\sigma_{\Pi_t^{Vol}}$.

In the literature (see, e.g., Ang and Chen (2002)), it has been widely demonstrated that it is possible to minimise the volatility of a portfolio using the correlation between the returns of securities belonging to different asset classes. In view of this, the previous model is augmented further by considering pairwise low correlations as a proxy of portfolio diversification with respect to asset classes, as it is typically performed within MPT to obtain the minimum variance portfolio (MVP). On each rebalancing date, the best assets in terms of momentum are retained in the portfolio whilst, if necessary, cash protection is activated to introduce a proportion of liquid assets. Next, all the non-cash assets are weighted according to the MVP principle. The momentum factor is here applied and considers the (low) pairwise correlations between the *NTop* assets and the volatility lookback as an additional model element. This element contributes to the specification of portfolio weights, as shown in Eq. (6) below, where assets are selected on the basis of the mom_t^i index introduced in Eq. (3). The fraction of liquidity is proportional to the number of best assets with unfavourable momentum and, additionally, the best $NPos_t$ assets are weighted with respect to their pairwise covariances to obtain the MVP. Notationally, the final PAAA portfolio (Π_t^{PAAA}) is defined as follows:

$$\Pi_t^{PAAA} = w_t^{cash} p_t^{cash} + \frac{NPos_t}{NTop_t} \Pi_t^{MVP} \tag{6}$$

where:

$$w_t^{cash} = 1 - \frac{NPos_t}{NTop_t};$$

$$\Pi_t^{MVP} = \sum_{i=1}^{NPos_t} w_t^i p_t^i;$$

$$w_t^i = \min_{w^i}(\sigma_{\Pi_t^{MVP}}) = \sum_{i=1}^{NPos_t} \sum_{j=1}^{NPos_t} w_t^i w_t^i \sigma_t^{i,j};$$

subject to:

$$1) w_t^i,\, w_t^j \geq 0, \qquad \text{for } i, j = 1, \cdots, NPos_t$$

$$2) \sum_{i=1}^{Npos_t} w_t^i = 1$$

The weight w_t^i of asset i at the rebalancing date t is defined according to the covariance between the returns of assets i and j, i.e.: $\sigma_t^{i,j}$. The portfolio allocation to the *Npos* best assets with low correlation is Π_t^{MVP}. This is weighted in proportion to the number of assets with favourable momentum and includes assets that minimise the volatility of the overall portfolio only. Again, the allocation of liquid assets is computed in advance as a fraction of *NTop* assets with unfavourable momentum.

2.5. Considerations and expectations about PAAA

According to the economic theory (e.g Andrew et al., 2006), rebalancing individual assets in a balanced portfolio on the basis of their corresponding recent volatility will lower the overall risk. Contrariwise, holding only assets with a positive price momentum is expected to increase the portfolio return (which could have been reduced by lowering the risk). Thus, combining price momentum, volatility balancing and cash protection should reduce the volatility of a portfolio but might have one of a variety of effects on the returns, namely: (a) reduced portfolio performance, (b) no effect on the portfolio performance, or (c) reduction in drawdowns induced by cash protection with a corresponding improvement in portfolio performance. In cases (b) and (c), portfolio performance would improve significantly, since each unit of risk has a higher return and, thus, risk is managed more efficiently. In case (a), the portfolio risk/return profile would improve if the return decreases less than the volatility.

Finally, diversification based on short-term correlations combined with cash protection would lead to the best risk/return profile. In this scenario, we can expect that the portfolio considering short-term 145 correlations realises a higher return per unit of risk. Since cash protection is introduced, we also expect PAAA to outperform AAA. For completeness, in the empirical analysis, we consider an alternative AAA portfolio based on the inclusion of a liquid asset in its universe. We expect PAAA to use the liquid asset more efficiently than AAA, as PAAA includes this asset in the portfolio only if the other assets have unfavourable momentums.

Table 1
Proxies of the ETFs used in Dataset 1 (see Appendix for details).

Market stocks	ETF	Target
US	SPY	S&P500
US	QQQ	Nasdaq100
US	MDY	S&P MidCap 400
US	IWM	Russel2000 Small Cap
Europe	FEZ	Euro Stoxx 50
Japan	EWJ	Japanese equity
Emerging Markets	EEM	Emerging Market Mid-Large Cap
Developed Market	EFA	Developed Market ex US & Canada
Global	SCZ	Small-cap developed mkt equities ex US and Canada
	Real Estates	
US	IYR	Composed index of US equities in RE sector
Global	RWX	DJ Global ex-U.S. Select RE Securities Ind.
	Commodities	
Global	DBE	5 energy-related futures contracts
Global	GLD	Gold bullion price
	Bonds	
US Gov.	TLT	Long US Treasury (20+ years)
US Gov.	IEF	Intermediate US Treasuries (7–10 years)
US Gov.	IEI	Intermediate US Treasuries (3–7 years)
US Gov.	SHY	Short US Treasuries (1–3 years)
Corporate High Yield	JNK	Barclays High Yield Very Liquid Index
Sovereign Emerging M.	EMB	Sovereign Bonds of 30+ Emerging Market
Liquidity (Cash protection)		
BND (CASH)		US Investment grade Bond Market

3. Benchmarking PAAA

3.1. Data

In our empirical analysis, we consider two datasets that include ETFs among the possible assets. We used ETF official data as far as possible. Alternatively, following Keller and Van Putten (2013), we created proxies that extend the ETF time series using data from both investment funds and similar ETFs.

In addition, we used a BND proxy that we call CASH for simplicity. Again, with reference to the work of Keller and Keller and Van Putten (2013), CASH is built using the fund VBMFX as a proxy for the BND fund. Data are observed on a daily basis and we focused on prices adjusted for dividends and splits. All prices are in US dollars and synchronised to the same dates for assets listed on different stock markets. Details about the data structure and time horizon are reported in the Appendix.

Dataset 1 (Table 1) presents ETFs that represent a well-diversified universe of activities observed from January 1995 to August 2016. Stock funds from several markets (US, Europe, Japan, emerging and global markets) are considered, as well as real estate funds, commodities funds (including gold) and several public and private bonds funds.

Fig. 1 shows the growth over time of the assets included in Dataset 1, and we can readily note that the growth rate differs for each asset, which highlights the fact that Dataset 1 contains assets belonging to different markets and sectors that are not excessively

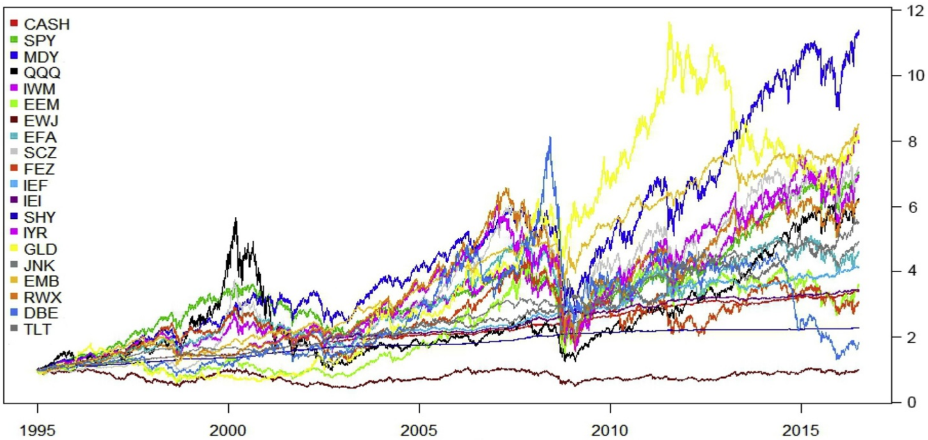

Fig. 1. Normalised prices at 1$. Growth rates of Dataset 1 assets prices (January 1995 - August 2016).

Table 2
Proxies of the ETFs used in Dataset 2 (see Appendix for details).

ETF S&P 500 sectoral indexes	Sector	Target
XME	Natural Resources	S&P Metals and Mining Select Industry Index
XLB	Natural Resources	S&P Materials Select Sector Index
XLE	Equity Energy	S&P Energy Select Sector Index
XLF	Financial	S&P Financial Select Sector Index
XLI	Industrials	S&P Industrial Select Sector Index
XLK	Technology	S&P Technology Select Sector Index
XLP	Customer Defensive	S&P Consumer Staples Select Sector Index
XLU	Utilities	S&P Utilities Select Sector Index
XLV	Health	S&P Health Care Select Sector Index
XLY	Consumer Cyclical	S&P Consumer Discretionary Select Sector IDX
	Liquidity (Cash protection)	
BND (CASH)		US Investment grade Bond Market

pairwise correlated.

The second dataset (Dataset 2), as shown in Table 2, contains a set of ETFs that replicate the sectoral indexes of the S&P 500 observed from October 1987 to August 2016. We considered the following industry sectors: natural resources, metals and raw materials, energy, financial, industrials 170 and technology, commodities and utilities, health and pharmaceutical. Although the assets comprising Dataset 2 represent a large range of activity sectors, the diversification possibilities are limited as these sectors are all subject to the long-term trend of the US stock market to which they belong.

Fig. 2 shows the growth over time of the assets in Dataset 2. The strong correlation between these assets is evident, with the only exception being CASH, which exhibits a smooth trend. Because of the restriction on any universe of assets that represent a limited variety of activities, we consider Dataset 2 to be an interesting benchmark against which to test PAAA.

3.2. Aims of the empirical analysis and calibration of model parameters

Our empirical analysis was aimed at assessing the actual benefits obtainable from PAAA through the quantification of the extra profit gained by its application. We assessed the effectiveness of PAAA in several tests, namely:

1) Assessment of the performance of PAAA on both datasets in order to account for different degrees of diversification.
2) Comparison of PAAA with a balanced benchmark over the full time horizon to assess the long-term validity of PAAA.
3) Comparison of the performances of PAAA and AAA over the full time horizon to evaluate the effectiveness of cash protection in the long term.
4) Comparison of PAAA, AAA and the balanced benchmark in both an in-sample and an out-of-sample analyses to account for the possible effect of data snooping.
5) Comparison of PAAA, AAA and the balanced benchmark using a rolling period approach, to evaluate the effectiveness of PAAA in both the mid-term and short-term perspectives.
6) Comparison of PAAA, AAA and the balanced benchmark over the time horizon covering the recent financial crisis, to evaluate the performances of these different strategies in a bear market scenario.

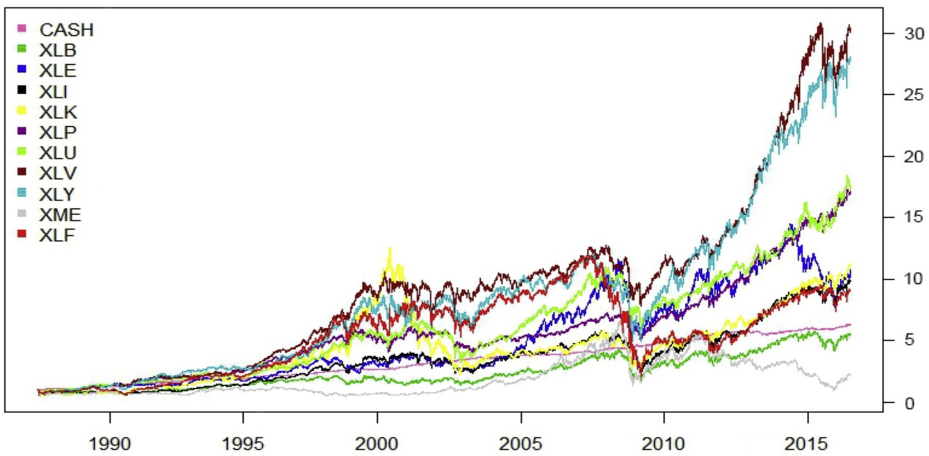

Fig. 2. Normalised prices at 1$. Growth rates of Dataset 2 assets prices (October 1987- August 2016).

The maximisation of the results obtainable from PAAA derives from a careful calibration of the model parameters. We tested the PAAA model on several periods of momentum lookback and volatility lookback: 3 to 12 months for the former and 15 days, 30 days and 60 days for the latter. An assessment of the combination of lookbacks that maximise the portfolio Sharpe ratio was followed by an assessment of the optimal fraction of assets to be turned in the portfolio. These investigations allowed us to specify the most effective combination of these parameters to be the following:

a) 9 months for the momentum look-back;
b) 1 month for the volatility look-back, and
c) a 50% fraction of the universe of assets to be turned in the portfolio.

To properly perform the in–out-of-sample analyses, we calibrated the parameters over the in-sample horizon only, and used the outcomes in the out-of-sample analysis. Thus, any data snooping concern has been dispelled. The short-term calibration of model parameters, particularly volatility, and the use of daily data in estimating momentum and volatility are consistent with the considerations expressed in Gosier et al. (2005) and allow the user to prevent some of the limitations of MPT highlighted in Michaud (1989). Moreover, using higher sampling frequencies to estimate the PAAA parameters significantly improves the accuracy of the covariance estimator used in the computation of portfolio weights (as highlighted, e.g., in Ardia and Boudt (2015)). Last but not least, following Støve et al. (2014), we used daily data when combining momentum, volatility and correlation (Section 2.4) to enable us to identify any asymmetries in the financial returns distributions and to account for the nonlinear dependency structure in bivariate data that would affect the pairwise correlations. In any case, to further confirm the validity of the results obtained from our direct comparison of PAAA and AAA, we computed volatility estimates on both a daily and weekly basis (see results in Table 4). The motivation for determining whether the use of different time intervals to compute asset volatility would affect portfolio performance is that volatility estimates based on daily data could be affected by the different time synchronicities of assets listed in many international markets. In this case, these estimates could be larger or noisier than those obtained from weekly data.

3.3. Results of the full time horizon analysis

The first goal of our analysis was a comparison of the performance of the PAAA portfolio with those obtained from the step-by-step derivation of PAAA (see Sections 2.2–2.4), namely: the balanced portfolio (*Balanced*), the volatility-weighted portfolio (*Volatility*) and the momentum-based portfolios, for which we selected assets on the basis of price momentum (*Momentum*) or volatility-

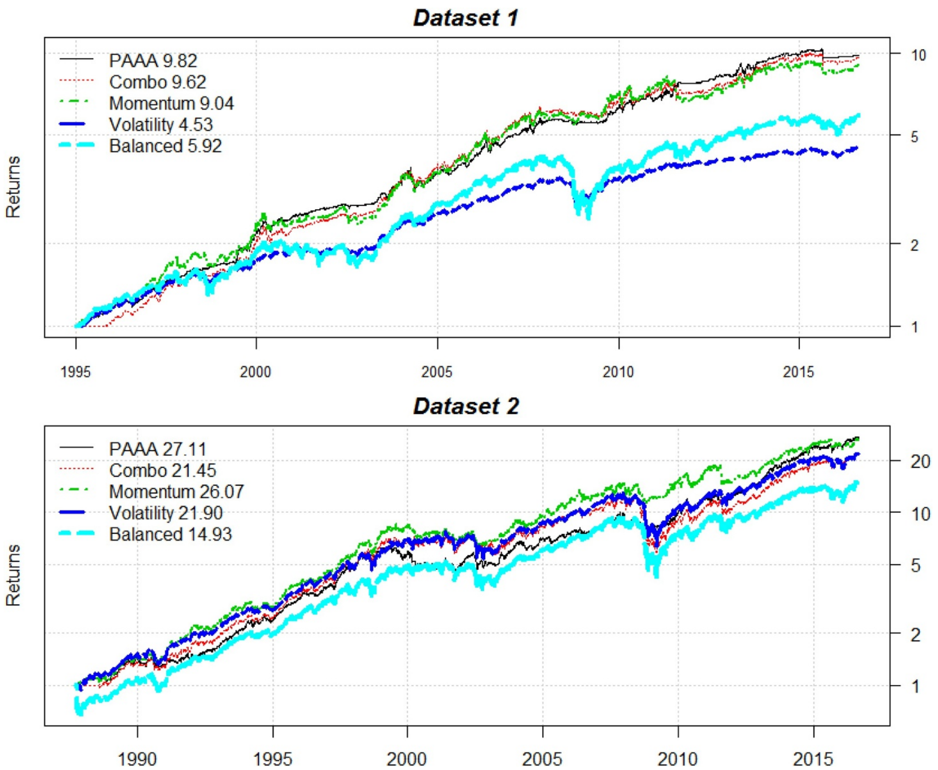

Fig. 3. Growth rate (log scale) over time of 1$ invested for assets of Dataset 1 (top panel) and Dataset 2 (bottom panel). *PAAA* is the portfolio defined in Eq. (6); *Balanced* is a naïve balanced portfolio; *Volatility* is a volatility-weighted portfolio; *Momentum* is a portfolio whose assets are weighted w.r.t. the momentum index introduced in Eq. (3) and *Combo* is a portfolio combining volatility weighting and momentum.

Table 3
Performance measures for different portfolios from Dataset 1 and 2. *PAAA* is the portfolio defined in Eq. (6); *Balanced* is a naïve balanced portfolio; *Volatility* is a volatility-weighted portfolio; *Momentum* is a portfolio whose assets are weighted w.r.t. the momentum index introduced in Eq. (3) and *Combo* is a portfolio combining volatility weighting and momentum.

Index Dataset 1	Balanced	Volatility	Momentum	Combo	PAAA
CAGR (in %)	8.57	7.23	10.71	11.03	**11.13**
Growth	5.92	4.53	9.04	9.62	**9.82**
Sharpe	0.76	1.36	1.02	1.20	**1.56**
Volatility (in %)	11.82	**5.24**	10.5	9.08	6.92
Max DD (in %)	−41.7	−19.32	−19.36	**−14.65**	−17.05
Avg DD (in %)	−1.60	**−0.79**	−1.91	1.46	−0.94
			Dataset 2		
CAGR (in %)	9.80	11.26	11.94	11.18	**12.09**
Growth	14.93	21.90	26.07	21.45	**27.11**
Sharpe	0.64	0.79	0.90	0.74	**0.98**
Volatility (in %)	16.82	14.92	13.48	15.97	**12.51**
Max DD (in %)	−54.54	−50.79	**−27.72**	−55.51	−32.89
Avg DD (in %)	−2.16	−1.88	−2.14	−2.14	**−1.74**

weighting (*Combo*). Fig. 3 shows the growth rates of the investment of 1$ in the different portfolios. Table 3 shows the same comparison with respect to the Compound Annual Growth Rate (CAGR) and other performance measures. The PAAA results seem to confirm those expected, as in both datasets it performs best in terms of the Sharpe ratio and returns, showing a marked improvement over the benchmark. As Fig. 4 shows, if we compare the drawdowns of the balanced and PAAA portfolios, the latter also appears to be the most convenient strategy in terms of average drawdown. We can argue that PAAA significantly reduces investment exposure to negative market cycles.

The last step of our full time horizon analysis is a direct comparison of the performances of AAA and PAAA. We applied AAA in two different versions; in the first (AAA), CASH is excluded from the universe, whereas it is included in the second (AAA Cash). This choice is made to dispel any doubt about the possibility that the simple inclusion of CASH in the AAA strategy could lead to the same results as those obtained by PAAA. As anticipated at the end of Section 2.5, we estimated asset volatilities on both a daily and weekly basis to account for possible bias in risk estimation arising from the consideration of only daily estimations.

Fig. 5 shows a comparison of strategies in terms of returns for the case in which volatility is estimated daily. As we can see in the figure, the investment grows more when managed using PAAA than using AAA in both versions and both datasets. In Dataset 2, the performance of SPY is also considered to extend the comparison to include a benchmark deriving from a stock market index. The plot obtained in the case of asset volatilities estimated on a weekly basis is identical to that in Fig. 5, but is not shown here due to space considerations. However, Table 4 shows the results obtained for both types of asset volatility estimation with respect to the main performance metrics. These metrics show that all the considered strategies outperformed the SPY index and that PAAA outperformed AAA in both datasets by at least 0.50% (0.90%) in terms of CAGR (Growth rate). In the case of a less diversified portfolio (Dataset 2), AAA with cash protection was able to further reduce volatility and drawdowns, thereby improving the risk/reward ratio.

4. Robustness checks

In the following, we present the results of some robustness checks. Since the results reported in Table 4 are very similar, whether asset volatility is estimated on a daily or weekly basis, here, we present the results of robustness checks for only the daily case.

4.1. In-sample and out-of-sample analysis

The results obtained in Section 3.3 confirm the effectiveness of PAAA with respect to standard portfolios and AAA, but they ignore any possible bias deriving from data snooping. To account for this possibility, we repeated the same analysis by partitioning the time horizon into two equally spaced and disjoint intervals. For both datasets, the time span captures different market movements and includes sub-periods characterised by financial crises. For Dataset 1 (Dataset 2), the in-sample horizon is from January 1995 to October 2005 (October 1987 to February 2002) and the out-of-sample horizon is from November 2005 to August 2016 (March 2002 to August 2016).

As for the in-sample analysis, Fig. 6 shows a comparison of the strategies in terms of their returns and reveals that the growth in the PAAA portfolio was greater than that of the other strategies in both datasets.

Table 5 presents the performance metrics, for which the results are similar to those obtained over the whole time period (Section 3.3): PAAA outperformed AAA and AAA Cash in both datasets by at least 0.25% (0.20%) in terms of CAGR (Growth rate). In the case of a less diversified portfolio (Dataset 2), AAA Cash further reduced volatility and drawdowns, thereby improving the Sharpe ratio.

The out-of-sample analysis enables us to verify the robustness of previously obtained results. Fig. 7 shows a comparison of different strategies in terms of returns, in which we can see that PAAA outperformed alternative strategies in both datasets. More

Table 4
Performance metrics for AAA and PAAA portfolios. *PAAA* is the portfolio defined in Eq. (6); *AAA* is the Adaptive Asset Allocation portfolio; *AAA Cash* is the AAA portfolio with a liquid asset included in its universe and *SPI* is the S&P 500 sectoral index. *D* indicates the estimation of asset volatility on daily basis and *W* indicates that on weekly basis.

Index	AAA		AAA cash		PAAA		SPY		AAA		AAA cash		PAAA	
	Dataset 1						*Dataset 2*							
	D	W	D	W	D	W	D	W	D	W	D	W	D	W
CAGR	10.63	(9.95)	10.52	(9.99)	**11.13**	(**10.20**)	9.41	(9.50)	11.10	(10.19)	11.36	(11.36)	**12.09**	(**11.68**)
Growth	8.91	(7.78)	8.71	(7.85)	**9.82**	(**8.19**)	14.78	(14.78)	21.00	(16.56)	22.48	(22.45)	**27.11**	(**24.41**)
Sharpe	1.39	(1.12)	1.50	(1.19)	**1.56**	(**1.22**)	0.58	(0.58)	0.85	(0.72)	**1.05**	(**0.95**)	0.98	(0.87)
Volatility	7.46	(8.82)	**6.84**	(8.29)	6.92	(**8.23**)	18.67	(18.67)	13.46	(15.09)	**10.83**	(**12.03**)	12.51	(13.82)
Max DD	−20.82	(−20.17)	−**17.05**	−(**19.83**)	−**17.05**	−(**19.83**)	−55.19	(−55.19)	−43.03	(−53.72)	−**23.39**	−(**25.07**)	−32.89	(−36.96)
Avg DD	−1.08	(−1.48)	−0.97	(−1.34)	−**0.94**	−(**1.29**)	−2.25	(−2.25)	−1.89	(−2.23)	−**1.66**	−(**2.01**)	−1.74	(−2.15)

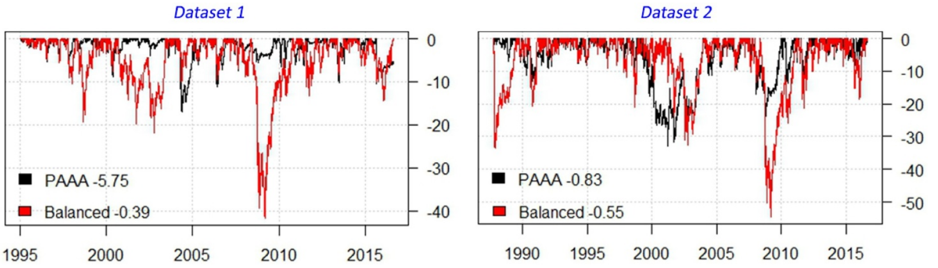

Fig. 4. Drawdowns of the Balanced portfolio and PAAA. *PAAA* is the portfolio defined in Eq. (6) and *Balanced* is a naïve balanced portfolio.

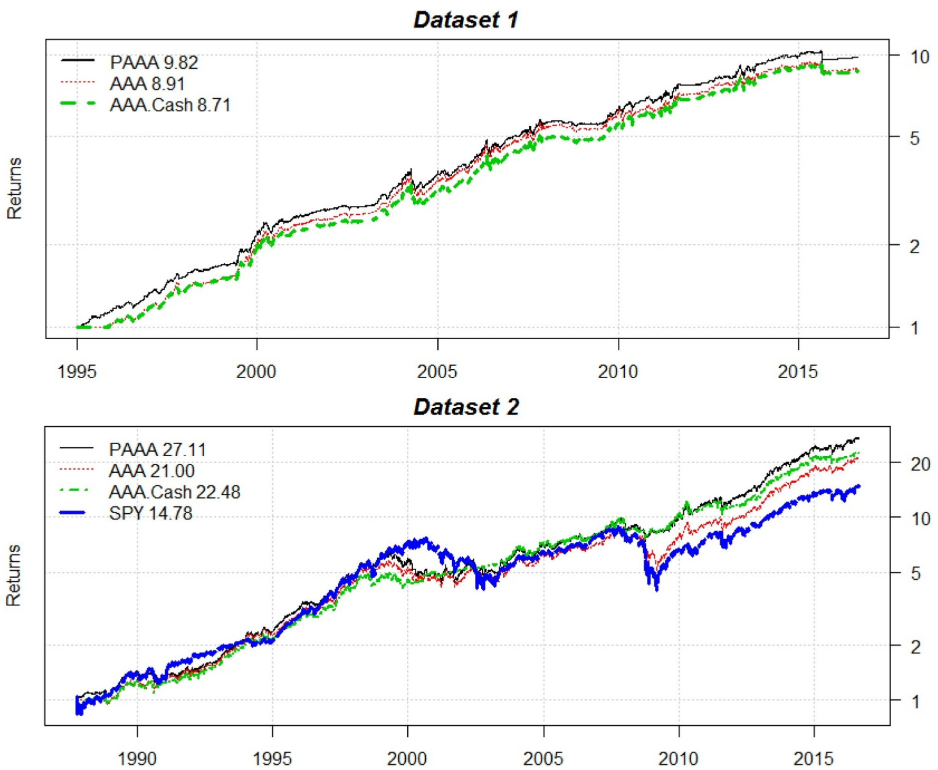

Fig. 5. Growth over time (log scale) of 1$ invested in each strategy on Dataset 1 (top panel) and Dataset 2 (bottom panel). *PAAA* is the portfolio defined in Eq. (6); *AAA* is the Adaptive Asset Allocation portfolio; *AAA Cash* is the AAA portfolio with a liquid asset included in its universe and *SPI* is the S&P 500 sectoral index.

interestingly, and contrary to the results of both the full-period and in-sample analyses, from Table 6, we can see that PAAA outperformed all competitors in both datasets with regard to CAGR and growth rate, as well as when the reference metric being considered was the Sharpe ratio. Thus, even in the case of a less diversified universe (Dataset 2), we could argue that the PAAA portfolio is the most reliable.

4.2. Rolling period analysis

Previous analyses have considered investment strategies spanning wide time horizons. However, Dalbar (2016) reported that, in the last 20 years, the average holding period of investors ranged between three and five years. This information prompted us to assess the behaviour of different strategies in shorter holding periods. For this reason, we performed a rolling period analysis, for which the reference metric was the percentage of victories obtained by each strategy in different sub-periods. We considered several winning indicators, including the number of times a portfolio achieved the best Sharpe ratio, how often a portfolio led to negative returns and a direct pairwise comparison of strategies to determine how many times they outperformed each other. To align our analysis with investor preferences, we considered holding periods of three and five years.

Table 7 shows the results obtained from the 3-yr rolling period analysis on both datasets, from which we can see that for both datasets PAAA achieved the lowest number of worst risk/return combinations, since its Sharpe ratio was always superior to least one of the other strategies. Accordingly, PAAA was the best strategy in terms of the 285 percentage of victories: 61.7% for Dataset 1 and

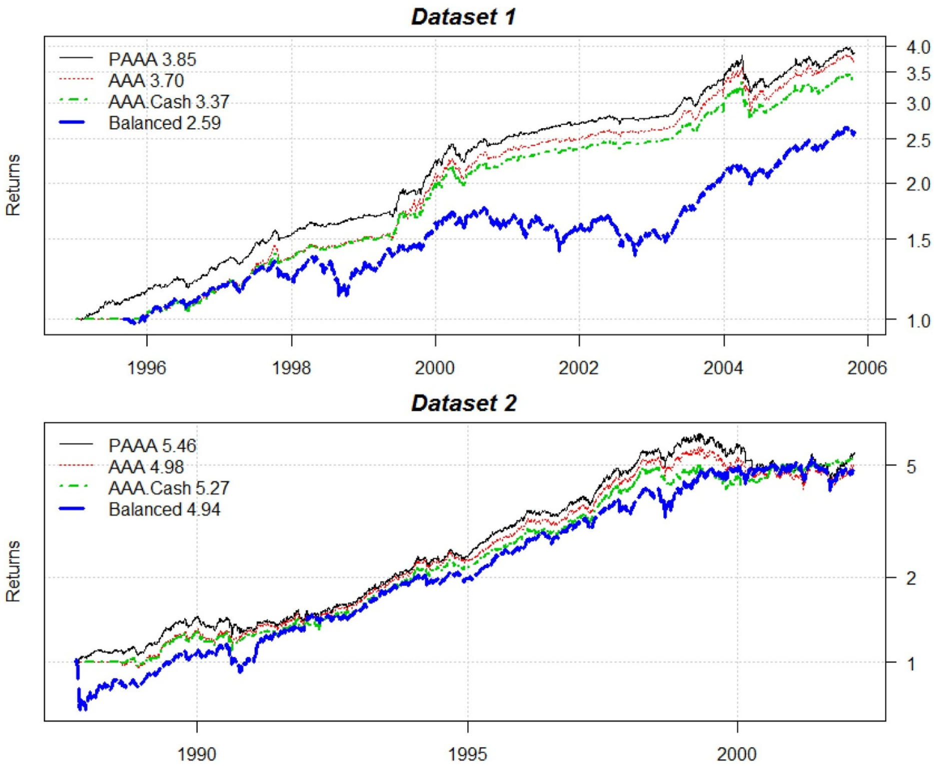

Fig. 6. Growth over time (log scale) of 1$ invested in each strategy on Dataset 1 (top panel: January 1995–October 2005) and Dataset 2 (bottom panel: October 1987–February 2002). *PAAA* is the portfolio defined in Eq. (6); *AAA* is the Adaptive Asset Allocation portfolio; *AAA Cash* is the AAA portfolio with a liquid asset included in its universe and *Balanced* is a naïve balanced portfolio.

Table 5
Performance metrics for AAA and PAAA in the in-sample analysis of Dataset 1 (January 1995–October 2005) and Dataset 2 (October 1987–February 2002). *PAAA* is the portfolio defined in Eq. (6); *AAA* is the Adaptive Asset Allocation portfolio; *AAA Cash* is the AAA portfolio with a liquid asset included in its universe and *Balanced* is a naïve balanced portfolio.

Index	Balanced *Dataset 1*	AAA	AAA cash	PAAA	Balanced *Dataset 2*	AAA	AAA cash	PAAA
CAGR	9.81	12.87	11.90	**13.28**	11.70	11.76	12.20	**12.47**
Growth	2.59	3.70	3.37	**3.85**	4.94	4.98	5.27	**5.46**
Sharpe	1.04	1.81	1.88	**2.05**	0.89	1.05	**1.24**	1.10
Volatility	9.45	6.84	**6.07**	6.19	13.39	11.17	**9.63**	11.27
Max DD	−21.86	−20.82	**−17.05**	**−17.05**	−33.45	−29.28	**−17.77**	−32.89
Avg DD	−1.50	−1.00	−0.89	**−0.84**	−2.12	−1.68	**−1.50**	−1.52

48.6% for Dataset 2 (94.5% and 82.6%, respectively, when considering it to be at least second best). Importantly, if we consider the performance of each strategy in the two datasets, the results are congruent for PAAA only.

Table 8 presents the results of the 5-yr rolling period analysis, which confirm that PAAA was rarely the worst strategy. Thus, results obtained in these two settings (3 yr or 5 yr) can be considered to be robust. In general, this direct comparison of strategies reaffirms the supremacy of PAAA. Considering the percentage of victories, PAAA achieved excellent results in Datasets 1 and 2 (65.1% and 47.2%, respectively) and was at least the second best performer in 95.4% (76.8%) of cases. Comparing these results with those obtained by other portfolios, we find that the best among them was AAA Cash, but it achieved a percentage of victories lower than 17% in both datasets.

4.3. Financial crisis period

Given recent developments in financial markets, with the onset of crisis and recovery, consistent with Marsh and Pfleiderer (2013) we focused our analysis on the financial–economic crisis period from 2007 to 2009. This analysis is important for two main reasons. First, it allows the assessment of the effectiveness of PAAA in an unfavourable period for investors. Secondly, it avoids the use of proxies for ETF data, thereby dispelling any residual concern about the relevance of results obtained from previous analyses into

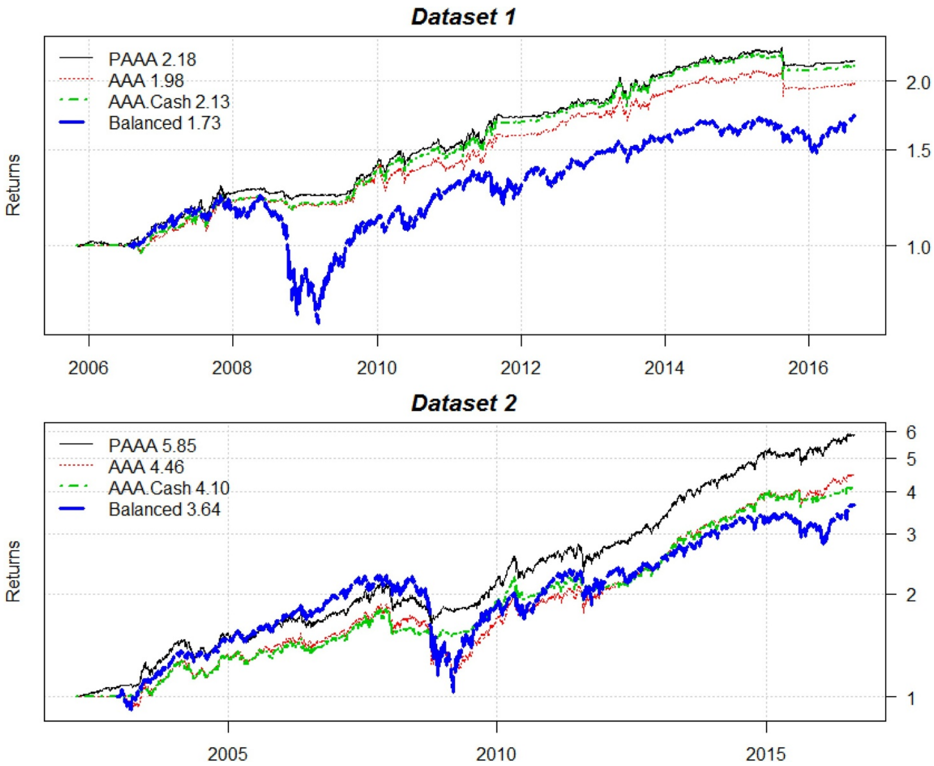

Fig. 7. Growth over time (log scale) of 1$ invested in each strategy on Dataset 1 (top panel: November 2005–August 2016) and Dataset 2 (bottom panel: March 2002–August 2016). *PAAA* is the portfolio defined in Eq. (6); *AAA* is the Adaptive Asset Allocation portfolio; *AAA Cash* is the AAA portfolio with a liquid asset included in its universe and *Balanced* is a naïve balanced portfolio.

Table 6
Performance metrics for AAA and PAAA in the out-of-sample analysis of Dataset 1 ((November 2005–August 2016) and Dataset 2 (March 2002–August 2016). *PAAA* is the portfolio defined in Eq. (6); *AAA* is the Adaptive Asset Allocation portfolio; *AAA Cash* is the AAA portfolio with a liquid asset included in its universe and *Balanced* is a naïve balanced portfolio.

Index	Balanced *Dataset 1*	AAA	AAA cash	PAAA	Balanced *Dataset 2*	AAA	AAA cash	PAAA
CAGR	5.57	6.49	7.22	**7.44**	9.87	10.86	10.23	**12.97**
Growth	1.73	1.98	2.13	**2.18**	3.64	4.46	4.10	**5.85**
Sharpe	0.45	0.89	1.06	**1.07**	0.58	0.77	0.88	**1.00**
Volatility	14.16	7.36	**6.80**	6.92	19.38	14.91	**11.87**	13.10
Max DD	−41.70	−10.82	**−10.41**	**−10.41**	−54.54	−43.03	**−23.39**	−25.59
Avg DD	−1.91	−1.15	−1.04	**−1.00**	−2.09	−2.15	−1.86	**−1.80**

Table 7
Performance measures for the rolling period analysis (holding period = 3 years). *PAAA* is the portfolio defined in Eq. (6); *AAA* is the Adaptive Asset Allocation portfolio; *AAA Cash* is the AAA portfolio with a liquid asset included in its universe and *Balanced* is a naïve balanced portfolio.

Sharpe ratio	Balanced Dataset 1	AAA	AAA Cash	PAAA	Balanced Dataset 2	AAA	AAA Cash	PAAA
Best(%)	16.4	5.5	23.4	**61.7**	28.2	3.6	24.6	**48.6**
1st or 2nd (%)	19.5	19.5	73.4	**94.5**	40.6	38.4	44.2	**82.6**
Worst (%)	78.1	13.3	5.5	**1.6**	54.4	10.9	29.0	**6.5**
Negative (%)	13.3	**0.0**	**0.0**	**0.0**	18.8	15.9	**0.0**	5.8
Balanced	–	75.0	78.9	83.6	–	64.5	69.5	68.1
AAA	25.0	–	81.2	92.2	35.5	–	44.9	87.7
AAA Cash	21.1	18.8	–	78.9	30.5	55.1	–	68.8
PAAA	16.4	7.8	21.1	–	31.9	12.3	31.2	–

Table 8
Performance measures for the rolling period analysis (holding period = 5 years). *PAAA* is the portfolio defined in Eq. (6); *AAA* is the Adaptive Asset Allocation portfolio; *AAA Cash* is the AAA portfolio with a liquid asset included in its universe and *Balanced* is a naïve balanced portfolio.

Sharpe ratio	Balanced Dataset 1	AAA	AAA Cash	PAAA	Balanced Dataset 2	AAA	AAA Cash	PAAA
Best(%)	12.8	1.2	20.9	**65.1**	20.0	1.6	31.2	**47.2**
1st or 2nd (%)	12.8	14.0	77.9	**95.4**	39.2	32.0	52.0	**76.8**
Worst (%)	84.9	12.8	2.3	**0.0**	49.6	29.6	16.8	**4.0**
Negative (%)	**0.0**	**0.0**	**0.0**	**0.0**	1.6	1.6	3.2	**0.0**
Balanced	–	76.8	53.1	87.2	–	56.8	76.6	66.4
AAA	23.3	0.0	87.2	95.4	43.2	0.0	56.0	91.2
AAA Cash	46.9	12.8	0.0	77.9	23.4	44.0	0.0	62.4
PAAA	12.8	4.6	22.1	0.0	33.6	8.8	37.6	0.0

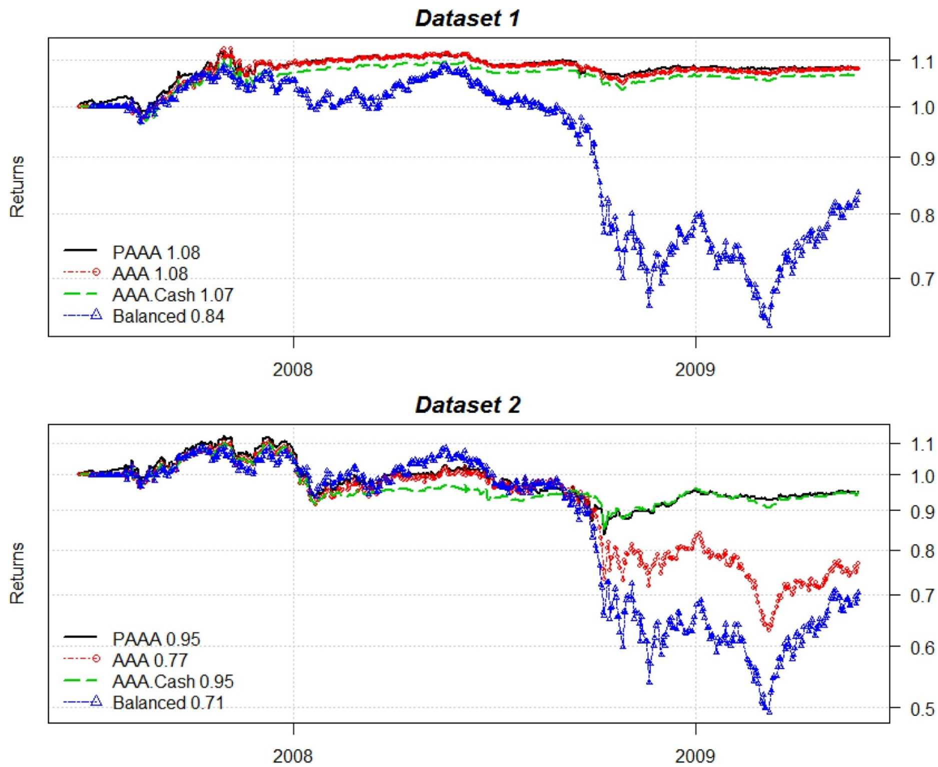

Fig. 8. Growth over time (log scale) of 1$ invested in each strategy during the financial crisis period(July 2007–May 2009) on Dataset 1 (top panel) and on Dataset 2 (bottom panel). *PAAA* is the portfolio defined in Eq. (6); *AAA* is the Adaptive Asset Allocation portfolio; *AAA Cash* is the AAA portfolio with a liquid asset included in its universe and *Balanced* is a naïve balanced portfolio.

Table 9
Comparison of strategies for the financial crisis period (July 2007–May 2009). *PAAA* is the portfolio defined in Eq. (6); *AAA* is the Adaptive Asset Allocation portfolio; *AAA Cash* is the AAA portfolio with a liquid asset included in its universe and *Balanced* is a naïve balanced portfolio.

	Balanced Dataset 1	AAA	AAA Cash	PAAA	Balanced Dataset 2	AAA	AAA Cash	PAAA
CAGR(%)	−8.94	3.00	2.52	**3.09**	−16.72	−9.49	−1.89	**−1.82**
Growth	0.84	**1.08**	1.07	**1.08**	0.71	0.77	**0.95**	**0.95**
Sharpe	−0.29	0.52	0.46	**0.53**	−0.33	−0.38	−0.12	**−0.07**
Volatility (%)	23.27	6.08	**5.79**	6.16	35.70	20.52	**10.84**	13.44
Max DD (%)	−41.70	−7.00	−6.26	**−5.56**	−54.54	−43.03	**−23.39**	−25.59
Average DD (%)	−4.75	−2.17	−2.26	**−1.52**	−9.38	−6.58	−4.39	**−3.15**

which some data approximation has been introduced. Thus, the data used in this analysis were official ETF data without any approximations. Fig. 8 provides a visual comparison of the performances of different strategies in the period from 1 July 2007 to 31 May 2009. Table 9 summarises the numerical results.

The results obtained for the financial crisis period clearly highlight the weaknesses of the naïve balanced strategy. The great riskiness of the balanced portfolio is evident in its more than tripled volatility than PAAA, as well as showing considerable maximum losses ranging between 41.7% and 54.5%. This level of loss requires that, to return to its previous value, the portfolio must regain between 71.5% and 120%, respectively, of its original value after the loss occurred. Once again, the best combination of risk and return was demonstrated by the PAAA portfolio. Specifically, we note that although PAAA had higher volatility, its risk profile was equivalent to that of the less risky AAA Cash portfolio, but the returns from PAAA were higher in both datasets. This result implies a superior Sharpe ratio for PAAA, which is probably due to the more focused use of the liquid asset arising from the more functional use of cash protection.

5. Concluding remarks

Protected Adaptive Asset Allocation (PAAA) is an alternative tactical asset-allocation strategy that generates superior risk/return results by using a momentum index to capture the short-run dynamics. PAAA accounts for cash protection during market downturn periods. We tested its effectiveness on two datasets containing portfolios formed from major market equity indices, real estate, commodities and bonds. Using common risk/return measures, we found PAAA to generally outperform other commonly used rebalancing techniques in a variety of scenarios.

Our basic motivation for the consideration of PAAA is that today many money managers are recommending that clients increase their cash holdings based on the argument that holding between 5% and 10% cash provides downside protection and the ability to rebalance effectively during negative market periods. At the same time, money managers argue that there continues to be support for the idea that momentum sends markets higher. This consideration is not new, having been expressed by Sharpe (2010), who attributed arguments against rebalancing to a relatively constant strategic asset allocation policy and suggested alternative strategies. He argued that rebalancing strategies do well in trendless environments and perform poorly in markets exhibiting momentum. In practice, Sharpe strongly suggested that high (low) realised returns forecast high (low) expected returns.

In this study, we evaluated the relevance of momentum and cash protection on two datasets for portfolios characterised by assets of different types and different levels of diversification. The results lead to interesting considerations. PAAA seems to improve upon both the balanced benchmark and AAA portfolios in terms of risk/return profile when applied on a well-diversified dataset in the long run. Consistent with previous literature that has considered momentum, PAAA provides higher returns with lower risk than a balanced portfolio. With regard to the naïve Adaptive Asset Allocation (AAA) with a liquid asset in the universe (AAA Cash), even if the risk profiles of the two strategies are quite similar, the returns generated by PAAA are always higher. We obtained this finding with respect to the long run, as confirmed by in/out-of-sample analyses, as well as during the financial crisis period. Thus, the results obtained in this paper can be placed alongside those of Keller and Van Putten (2012), Antonacci (2012), Keller and Butler (2014) and Keller and Keuning (2016), who found performance to improve by the introduction of liquidity-based protections.

When the universe is less diversified and, in specific cases, contains assets that replicate a sectoral equity index (like S&P), the results differ slightly. Although PAAA considerably improves the balanced benchmark and a Buy&Hold portfolio built on SPY 500, it does not systematically provide a better risk/return combination than AAA Cash. Specifically, even if in every mid-long-term application the PAAA returns are the highest, its volatility is higher than that of AAA Cash, which sometimes leads to a worse risk/return combination. We stress that these are only very slight differences that leave the two strategies essentially at the same performance level.

In view of the results obtained for the two datasets, we can say that PAAA is preferable to the balanced and Buy&Hold portfolios, and is a valid alternative to AAA since it leads to higher returns with an equivalent risk profile. However, this conclusion is appropriate only for long period analysis. Any short period analysis provides evidence for a net preference for PAAA. These comparisons were based on the number of times each strategy performed the best or the worst. We observed that most of the time the balanced portfolio yielded the worst results and that, in contrast, PAAA exhibited a significantly higher number of wins than the other models. Thus, regardless of the time period in which the investment is made, we found PAAA to more frequently outperform the other strategies. Interestingly, the number of negative (worst) results for PAAA in our study was extremely low, which serves as a sort of warranty for a risk adverse investor.

Nevertheless, we must highlight some limitations of PAAA. We did not consider transaction costs or the fees and frictions of the market in this analysis. Although we selected the proxies we used from funds that include commissions and transaction costs, to deepen this analysis, it will be appropriate to consider this aspect in more detail. It is well known that frictions, fees and taxes can significantly reduce the advantage of adopting an active strategy over a naïve strategy that require little in the way of rebalancing over time. The impact of these effects is a research aspect we plan to develop in the near future.

In conclusion, we emphasise that the expectations for the proposed model were met, as PAAA showed better results than less active portfolio strategies. PAAA represents a valid alternative to the AAA approach on which it is partly based, both in the long and short runs, but mostly with respect to the period corresponding to the average holding period for an investment.

Appendix. Information about Dataset 1 and Dataset 2

Structure of Dataset 1. The symbol + indicates proxies.

Proxy	Ticker	Description	Time availability
SPY +	SPY	SPDR State Street Global Advisors	January 1993
SPY +	VFINX	Vanguard	January 1980
QQQ +	QQQ	PowerShares	March 1999
QQQ +	KTCAX	Deutsche Asset & Wealth Mngt	January 1980
MDY +	MDY	SPDR State Street Global Advisors	August 1995
MDY +	FMCSX	Fidelity Investments	March 1994
MDY +	FDVLX	Fidelity Investments	January 1980
IWM +	IWM	iShares	May 2000
IWM +	NAESX	Vanguard	January 1980
FEZ +	FEZ	SPDR State Street Global Advisors	October 2002
FEZ +	FIEUX	Fidelity Investments	October 1986
EWJ +	EWJ	iShares	April 1996
EWJ +	FJPNX	Fidelity Investments	September 1992
EEM +	EEM	iShares	April 2003
EEM +	VEIEX	Vanguard	May 1994
EEM +	FEMKX	Fidelity Investments	October 1990
EFA +	EFA	iShares	August 2001
EFA +	FDIVX	Fidelity Investments	December 1991
SCZ +	SCZ	iShares	December 2007
SCZ +	DLS	WisdomTree	June 2006
SCZ +	PRIDX	T.Rowe Price	December 1988
IYR +	IYR	iShares	June 2000
IYR +	VGSIX	Vanguard	May 1996
IYR +	FRESX	Fidelity Investments	November 1986
RWX +	RWX	SPDR State Street Global Advisors	December 2006
RWX +	VNQ	Vanguard	September 2004
RWX +	VGSIX	Vanguard	May 1996
RWX +	FRESX	Fidelity Investments	November 1986
DBE +	DBE	PowerShare DB	January 2007
RWX +	GSP	Barclays Funds	June 2006
RWX +	USO	United States Commodity Fund LLC	April 2006
RWX +	MAGRX	BlackRock	October 1988
RWX +	PSPFX	US Global Investors	July 1983
GLD +	GLD	SPDR State Street Global Advisors	November 2004
GLD +	SCGDX	Deutsche Asset & Wealth Mngt	September 1988
TLT +	TLT	iShares	August 2002
TLT +	VUSTX	Vanguard	May 1986
IEF +	IEF	iShares	July 2002
IEF +	VFITX	Vanguard	October 1991
IEI +	IEI	iShares	January 2007
IEI +	VFITX	Vanguard	October 1991
SHY +	SHY	iShares	July 2002
SHY +	VFISX	Vanguard	October 1991
JNK +	JNK	SPDR State Street Global Advisors	December 2007
JNK +	HYG	iShares	April 2007
JNK +	FAHYX	Fidelity Investments	January 1987
EMB +	EMB	iShares	December 2007
EMB +	PREMX	T.Rowe Price	December 1994

Structure of Dataset 2. The symbol + indicates proxies.

Proxy	Ticker	Description	Time availability
XME +	XME	SPDR State Street Global Advisors	June2006
XME +	VGPMX	Vanguard	May 1984
XLB +	XLB	SPDR State Street Global Advisors	December 1998
XLB +	FSDPX	Fidelity Investments	October 1987
XLE +	XLE	SPDR State Street Global Advisors	December 1998
XLE +	VGENX	Vanguard	May 1984

XLF +	XLF	SPDR State Street Global Advisors	December 1998
XLF +	FIDSX	Fidelity Investments	December 1981
XLI +	XLI	SPDR State Street Global Advisors	December 1998
XLI +	FSCGX	Fidelity Investments	October 1987
XLK +	XLK	SPDR State Street Global Advisors	December 1998
XLK +	FSPTX	Fidelity Investments	July 1981
XLP +	XLP	SPDR State Street Global Advisors	December 1998
XLP +	FDAFAX	Fidelity Investments	July 1985
XLU +	XLU	SPDR State Street Global Advisors	December 1998
XLU +	FSUTX	Fidelity Investments	December 1981
XLV +	XLV	SPDR State Street Global Advisors	December 1998
XLV +	VGHCX	Vanguard	May 1984
XLY +	XLY	SPDR State Street Global Advisors	December 1998
XLY +	FSRPX	Fidelity Investments	December 1985

Structure of proxies used as liquid asset for Cash Protection.

Proxy	**Ticker**	**Description**	**Time availability**
CASH	BND	Vanguard	April 2007
CASH	VBMFX	Vanguard	December 1986

Supplementary material

Supplementary material associated with this article can be found, in the online version, at 10.1016/j.frl.2019.01.007.

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