Protective Asset Allocation (PAA);
A Simple Momentum-based Alternative for Term Deposits

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Abstract

Since the financial crisis of 2008 and the recent (end of 2015) pull back, investors are searching for less risky investments. Therefore, there is a growing demand for low risk / absolute return portfolios. In this paper we describe a simple dual-momentum model (called Protective Asset Allocation or PAA) with a vigorous "crash protection" which might fit this bill. It is a tactical variation on the traditional 60/40 stock/bond portfolio where the optimal stock/bond mix is determined by multi-market breadth using dual momentum. We backtested the model with several global multi-asset ETF-proxies. Starting from Dec 1970 allows us to investigate the behavior of PAA in periods with rate hikes as well. The in-sample (Dec 1970 – Dec 1992) and out-of-sample returns of the most protective variant of our PAA strategy satisfy our absolute return requirement without compromising high returns. This makes PAA an appealing alternative for a 1-year term deposit.

1. Introduction

Since Faber (2007) and the recent financial crisis (2008/2009), there is a renewed interest in trend following. Faber showed how an SMA (Simple Moving Average) filter of asset prices can improve not only the risk but also the returns by skipping bear markets and other drawdowns. The recipe is simple: move to cash for as long as the most recent price is below the SMA trend, which is often based on the average of the last 10 monthly prices (SMA10). This also explains the name trend following (or timing). Trend following is also called *absolute momentum*. Instead of using an SMA filter, the 12-month (or any other lookback length within a year) price return (RET12) could also be used as trend indicator (Moskowitz, 2011, Antonacci, 2013a). Again, one moves to cash as long as the return over the lookback period is negative.

The mechanism behind trend following is that of "momentum" or "price persistence" where rising prices will continue to rise and falling prices will get even lower. Several academic studies (e.g. Jegadeesh, 1993) have shown momentum to be relevant as long as the lookback period is between one month and one year. When the lookback period becomes much larger (say 60 months) or much shorter (less than a month) the opposite happens and we speak of "reversal". So momentum and reversal are opposite effects, depending on the length of the lookback period.

Besides absolute momentum, there is also *relative (or cross-sectional) momentum*. In this case momentum is compared between assets, often using the return over say the last twelve months. Next the assets with the highest relative returns (e.g. the best Top3 assets out of a universe with 12 assets) are selected for investment. This explains its name: relative momentum. And since each month different

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assets may show up in the Top selection, one “rotates” these assets over the months depending on their relative momentum (or “relative strength”), assuming monthly portfolio reformations (see e.g. Fama, 1993, Faber, 2010, and Asness, 2014).

So absolute momentum often implies the application of a trend filter overlay (using e.g. a 10-prices Simple Moving Average SMA10 or a 12-month return filter RET12) while replacing assets by cash when the trend is negative. Relative momentum implies choosing the Top performing assets (in terms of e.g. a 12-month return) out of the N assets in the universe with Top << N.

Antonacci (2013b) coined the phrase "dual momentum" for a combined absolute and relative momentum scheme which were both based on the 12-month return (in excess of the risk-free rate). Keller (2012) did something similar but with the 4-month return for both absolute and relative momentum in his Flexible Asset Allocation (FAA). Sometimes both trend indicators (SMA and RET) are mixed, like in Faber (2013) where a trend filter (absolute momentum) based on a SMA10 is combined with rotation (relative momentum) based on the average return over 1, 3, 6 and 12 months.

Our momentum model is mainly inspired by Faber and Antonacci and many others who wrote about absolute and relative momentum. The interested reader is referred to Antonacci (2014), Newfound (2015) and Faber (2013) for a historical overview. In this paper we will use a similar dual-momentum strategy as adopted by Faber and Antonacci, but based on an SMA trend filter for both types of momentum.

In addition, we will use a vigorous *“crash protection”* by moving all capital to “cash” (or better: safe treasury bonds) when global markets becomes more bearish. We will use a multi-market breadth indicator to measure the market regime globally. We will call this strategy *Protective Momentum*. We think that this crash-protection mechanism is the main innovation of our paper. As such, protective momentum can also be applied to various other momentum models with only absolute or relative momentum (Faber, 2007, 2010) or generalized momentum (e.g. Keller, 2012, 2014b) to improve risk adjusted returns. In this paper we will combine protective momentum with a simple dual momentum model, based on SMA, to arrive at the *Protective Asset Allocation (PAA) strategy*. We will distinguish between low (PAA0), medium (PAA1) and high protection strategies (PAA2), depending on the chosen protection rate (a=0,1,2, resp.).

Using a multi-market breadth indicator for crash protection is a simple extension of the crash-protection in traditional dual momentum models. It is based on the idea that crash-protection by trend following can also be applied to the universe instead of to individual assets. In other words, due to correlation among assets, not only an asset’s own momentum but also the momentum of other assets in the universe could provide useful information for the required amount of crash-protection.

Furthermore our indicator allows for heavier protection than in traditional dual-momentum strategies as can easily be seen. Take, for example, an N=12 universe with a 6-asset rotation based on momentum. Only when some of the Top6 assets have non-positive momentum, these assets are moved to cash in traditional dual-momentum strategies. In contrast, in our most protective momentum approach (PAA2), we can move e.g. 100% to cash when all Top6 assets have positive momentum and all other six assets have non-positive momentum. So our protective momentum can be much more aggressive in moving to cash. This turns out to be not only good for risk reduction but even for returns. Here “limit your losses” helps to reduce risk and even to improve returns (relative to the 60/40 benchmark), as we hope to demonstrate in this paper.

To compete with one-year term deposits, we define “*absolute return*” strategies to have 95% of the 1-year rolling returns not below 0% and 99% not below -5%. As we will show below, the most-protective PAA strategy (PAA2) with a global multi-asset universe with twelve ETF-proxies and one or more treasury ETF-proxies as “cash”, has “absolute-returns” both in- as well out-of-sample over 45 years (Dec 1970-Dec 2015). We also compare our results with the near-passive 60/40 stock/bond mix and the traditional dual-momentum model. We will conclude that risk is severely reduced while return is even better than 60/40, resulting in better Sharpe ratios and much smaller drawdowns. By including the rising-rates period of Dec 1970 – Dec 1981, we also show that PAA2 is able to perform well when treasury yields go up. We demonstrate this for various (combinations of) “safe treasuries”.

The outline of the paper is as follows. In section 2 the model is introduced. In sections 3 and 4 we look at the in-sample (IS) and out-of-sample (OS) performance, respectively. We consider alternative safe bonds (as “cash”) in section 5. Section 6 concludes.

2. The PAA model

Both kinds of momentums (absolute and relative) rely on some lookback period often less or equal to a year. The SMA filter signals a positive trend when the latest price p0 is above the SMAx level, where x is the number of past prices which are averaged. Popular values for SMA filters are x=200 daily prices and 10 or 12 monthly prices. The simpler return momentum filter does the same when the return RETy is positive over y-periods, where y is the length of the lookback period in number of days, weeks or months. Besides the 12-month return momentum, average returns over 1, 3, 6 and 12 months are also common as momentum measures, see Faber (2013), Hurst (2012), and Keller (2014b, 2015). Notice that with SMAx the x monthly prices (points) averaged corresponds to x-1 months (intervals).

For PAA we are combining the methods of Faber and Antonacci by using the same SMA both for trend following as well as for rotation. By doing so, we stay in line with the dual momentum approach of Antonacci, but with an SMA filter instead of an (excess) return (RET) filter. In the following we will use the same lookback parameter L for both and write SMA(L) and RET(L) indicating a lookback period expressed in time units. Since we will be using monthly data, the lookback L always refers to L months. So e.g. SMA10 (of 10 prices) is equivalent to SMA(9), with a 9-months lookback period.

Beekhuizen (2015), Zakamulin (2015a) and Levine (2015) demonstrate that SMA and RET filters (and some others, like EMA and MACD) can all be expressed as a simple function of some weighed average of monthly price returns. E.g. RET(12) is based on an equal-weight filter over the previous 12-monthly returns, while SMA(12) is based on a linearly decreasing weight filter over the previous 12-monthly returns (so the most recent month return is weighted 12 times, the month before 11 times, up to the oldest (12th) month one time). Zakamulin (2015b, c) shows that among many alternatives the SMA filter is one of the most robust and nearly identical to an Exponential Moving Average filter. The average

1/3/6/12 month return filter used by Faber and others can also be shown[2] to be similar to the downward sloping weight shape of the SMA12 filter although with a less gradual decent of the return weights.

The dual-SMA-momentum approach is the basis of our Protective Asset Allocation (PAA) model, together with a vigorous crash protection where the bond fraction is increased in bear markets using a multi-market breadth indicator, as we will explain below.

Our momentum indicator is based on the SMA(L) filter and the most recent asset price p0:

$$MOM(L) = p0/SMA(L) - 1 \quad (1)$$

L is the length of the lookback period in months. Assets can also be compared with other assets by their relative MOM(L) score for rotation (relative momentum or -strength). Trend following (absolute momentum) will be ruled by the sign of MOM(L), hence, besides safe assets like treasuries or cash, only assets with positive momentum will be used in the portfolio.

Normally, in absolute momentum (trend following) studies, assets with non-positive momentum are replaced by risk-free "cash" such as T-bills. We will, however, use a more bond-like cash proxy by using the exchange traded intermediate (7-10y) treasury bond fund IEF (like we did in Keller, 2014b). The deployment of IEF has two advantages over risk-free cash: we can often make higher returns with a treasury fund as our "safe" asset while a treasury fund also acts more as a "hedge" to the risky assets in periods of market turmoil, because of their low beta. [3] See section 5 for the use of alternative treasury bonds with shorter duration as "safe bonds".

[2] Since the x=1,3, 6 and 12 months RETx have monthly return weight vectors proportional to (100000000000), (111000000000), (111111000000), and (111111111111) resp., one can see that the weights for the 1/3/6/12m return average are proportional to their sum, so to (4,3,3,2,2,2,1,1,1,1,1,1) instead of (12,11,10, ..,1) for the SMA(12) filter (see Beekhuizen, 2015).

[3] An additional advantage of IEF over slightly shorter treasury ETFs (like IEI) is its better liquidity.

The hedge-return character of IEF is demonstrated in the recent pull back (see Fig. 1). Notice that the Fed increased rates at Dec 15, 2015, which might imply lower bond prices. However, because of the market turmoil, the prices of treasury funds like SHY (1-3y), IEF (7-10y) and TLT (20+y) went up due to their usage as safe havens. This figure also shows why IEF is such a suitable “safe” bond: it is a much better hedge than SHY (5.3% vs. 0.6% return), while less risky than TLT (5.7% vs. 13.9% volatility).

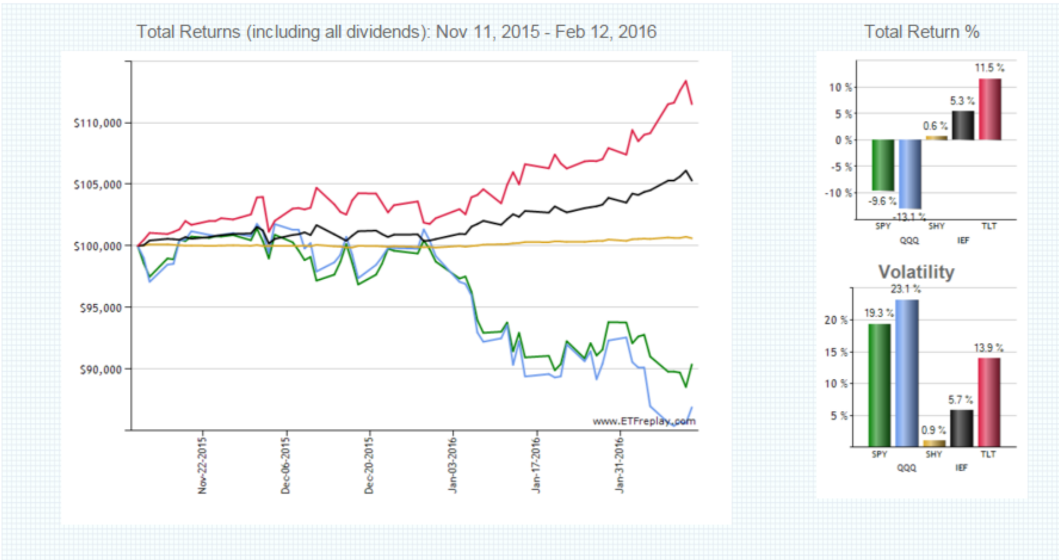

Fig. 1 Total returns Nov 11 2015 – Feb 12 2016 (© ETFReplay.com)

Before we present the recipe of our simple PAA model, we have to define our universe. We will use a global multi-market universe as a replacement for stocks in the traditional 60/40 stock/bond mix, with IEF in the “safe” bond role. Therefore our universe will focus on “risky” assets, like the stocks in the 60/40 mix but now with an active mix instead of a fixed 60/40 allocation (and global assets classes instead of stocks).

The optimal mix of “risky” assets will be determined by the dual momentum model. The optimal Bond Fraction (BF) is determined by the market regime which is measured by the multi-market breadth. So BF will therefore determine the balance between the risky and the bond (IEF) part of our capital allocation, with monthly reformations.

For the risky assets we will follow Faber (2013) with a global multi-assets universe of twelve ETFs, including some risky bonds like TLT[4], HYG and LQD. The number of assets in the (risky) universe will be denoted N (=12). As said, for now the “safe” treasury bond part consists solely of the 7-10y treasury bond fund IEF.

Before disclosing the PAA recipe we have to define “good” and “bad” assets. There are n *good* assets with a positive momentum, so MOM(L) > 0, n<=N. The remaining (N-n) assets (with MOM<=0) are the *bad* assets. We will simply use the number of good/bad assets as a regime indicator: more bearish when

[4] Due to its high volatility (see Fig. 1) we do not consider TLT suitable as safe harbor haven.

n is low, more bullish when n is high relative to N. This indicator applied to stocks is often called the “breadth” of the market. Since we apply it to assets, we will call it the “multi-market breadth” indicator.

Having defined all necessary ingredients, we are now able to give the recipe for our PAA model:

1. Compute the *bond fraction* BF depending on the number of good assets n:

   $$BF = (N-n)/(N-n1), \quad \text{with } n1 = a*N/4, \tag{2}$$

   where a is the *protection factor* (a>=0) and BF=100% if n<=n1.
2. Determine the Top (Top<=N) good assets with the highest momentum to form the risky (stock-like) part of the portfolio with equal weights (EW) for each risky asset. If n<Top, only the n good assets (with positive momentum) will be included in this risky EW portfolio.
3. Mix the risky EW portfolio with the bond part in a (1-BF)/BF fashion, like with the 60/40 strategy.

Notice that the higher the protection factor a is, the higher is n1 (with BF=100% if n<=n1) and therefore by increasing a, the bond fraction BF will become higher for the same number of good assets n. Notice also that our portfolio is *long-only*, and *equal-weight,* except for the bond part (which fraction is determined by eq. (2)).

In the following we will focus on three sub models of PAA with protection factors a=0, 1 and 2. When a=0, 1 or 2 we will describe the protection level as *low, medium or high* respectively. We will denote these models by PAA0, PAA1 and PAA2 respectively.

The low-protective PAA model arises when the protection factor is set to a=0. Then the bond fraction BF equals the fraction of bad assets in the *full* (risky) universe, i.e. BF=(N-n)/N. So with e.g. n=6 and N=12, the bond fraction becomes BF=50%. Only when all assets are bad (n=0) the bond fraction becomes 100%. We will call this the *low-protection* PAA model, denoted by PAA0. Notice that this low protection model (a=0) is similar to the crash-protection model in Keller (2014b).

When the protection factor is dialed up to a=1, the bond fraction BF equals the fraction of bad assets relative to *three-quarters of size of the risky universe* (so 0.75N), i.e. BF=(N-n)/(0.75N), with a maximum of 100%. So with e.g. n=6 and N=12, the bond fraction becomes BF=6/9=67%. This also implies that with 75% or more bad assets in the universe, the bond fraction becomes 100%. We will call this the medium-protection PAA model, denoted by PAA1.

The most protective PAA model is obtained with the protection factor set to a=2. Then the bond fraction BF equals the fraction of bad assets relative to *half of size of the risky universe* (so 0.5N), i.e. BF=(N-n)/(0.5N), with a maximum of 100%. This also implies that with 50% or more bad assets in the universe, the bond fraction becomes 100%. So with again e.g. n<=6 and N=12, allocation of 100% of capital will go to our safe haven fund IEF since BF=100%. We will call this the high-protective PAA model, denoted by PAA2. It is this PAA2 model which we consider our alternative for a 1-year term deposit.

In Fig. 2 we show the bond fractions BF for the case of a (risky) universe with size N=12 for various number of good assets n=0,1,…12 (and therefore with N-n bad asset) as a function of the protection factor a=0,1,2 (low, medium, high protection).

#Bad	12	11	10	9	8	7	6	5	4	3	2	1	0
#Good	0	1	2	3	4	5	6	7	8	9	10	11	12
a=0	100%	92%	83%	75%	67%	58%	50%	42%	33%	25%	17%	8%	0%
1	100%	100%	100%	100%	89%	78%	67%	56%	44%	33%	22%	11%	0%
2	100%	100%	100%	100%	100%	100%	100%	83%	67%	50%	33%	17%	0%

Fig. 2 Bond fractions BF as a function of a (a=0,1,2), vs. number of good (n) and bad assets (N=12)

As is clear from Fig. 2 the bond fraction BF soon becomes very dominant when the high-protective (a=2) model is applied, where 6 (out of N=12) or less good assets result in a 100% bond coverage, while even with 9 (out of N=12) good assets the bond coverage is already 50%. Exclusively when there are only good assets (n=12, so all assets of the risky universe have positive momentum), the bond coverage is zero.

Although in this paper we will use the multi-market breadth protection strategy as given by eq. (2) only in combination with a very simple dual (SMA based) momentum strategy, we might as well combine it with other tactical strategies like FAA (Keller, 2012), EAA (Keller, 2014b) and even CAA (Keller, 2015). In that context, we suggest the name "*protective momentum*".

3. Data and In-Sample optimization

We will backtest the PAA models described above using monthly ETF-proxies from Dec 1970 – Dec 2015 (45 years). We will use a global multi-asset "risky" universe consisting of proxies for the following N=12 ETFs:

- SPY, QQQ, IWM (US equities: S&P500, Nasdaq100 and Russell2000 Small Cap, respectively),
- VGK, EWJ (Developed International Market equities: Europe and Japan, respectively),
- EEM (Emerging Market equities),
- IYR, GSG, GLD (alternatives: REIT, Commodities, Gold, respectively.),
- HYG, LQD and TLT (High Yield bonds, Investment Grade Corporate bonds and Long Term US Treasuries, respectively.).

The "safe" bond will be represented by IEF (7-10y, Intermediate US Treasuries), as in Keller (2014b). For the risk-free (rf) rate we will use the return on BIL (2-3m, T-bills). Besides IEF, we also considered a larger bond universe (BIL, SHV, SHY, IEI, IEF, TLT, AGG) as "safe" bonds in section 5.

All data is from free or near-free sources (MSCI, ALFRED, REIT, PremiumData, StockCharts, Ibbotson SBBI, Fama French and Yahoo), see Appendix A. All basic data consists of end-of-month adjusted (total return) prices (adjusted for dividends, splits, etc.), excluding dividend taxes (gross). For creating our ETF-proxies, some treasury bond ETFs like IEF (7-10y) and TLT (15y+) are constructed[5] from several constant maturity bond series obtained from ALFRED. All ETF-proxies (based on indexes) are constructed to minimize the tracking error with the (recent time) overlapping performance of the corresponding true ETFs and therefore include management fees. Data construction is also described in detail in Appendix A. We will denote our "risky" universe as the N12 universe. The inception month for all ETF-proxies is Dec 1969 with for each a starting price of $100.

Since we need a lookback period of twelve months in our PAA recipe, our backtest can start in Dec 1970 and ends Dec 2015. In order to test for data snooping we will split the data is two parts: Dec 1970 – Dec 1992 (in-sample period: IS) and Dec 1992 – Dec 2015 (out-of-sample period, OS). We have chosen the IS period such that it contains both a period with a regime of overall rising rates (from Dec 1970 – Dec 1981) and one with a regime of overall decreasing rates (Dec 1981 – Dec 1992) of equal length (each 11 years). This allows us to train the PAA model in both circumstances. In fact, we will optimize the parameters (rotation Top, lookback L and the degree of protection a) over the IS period and test the best IS parameters over the OS period. Like Keller (2014b), we will assume a (one-way) transaction fee of 0.1%, which might be too low for the first years (1970-) but too high for the last years (-2015).

In order to compare the scenarios over IS, we will need performance measures. We will look at all the usual performance measures like return R (CAGR), V (annual Volatility), D (max Drawdown), SR (Sharpe Ratio above the risk-free return) and MAR (=R/D).

In addition, we will focus on the 1-year-rolling-return Win-rate (denoted Win0), since we are comparing PAA with a (1-year) term deposit. We aim at a Win0 score of at least 95%, so out of all consecutive twelve months periods over the test period a maximum of only 5% may have a negative return and is therefore considered worse than a 1-year deposit. And as we will see, the average return of our PAA2 model is much higher than a 1-year deposit to compensate for this small (5%) chance of loss.

To get a grip on the 1y-rolling *negative* returns, we will also look at the fraction (denoted Win5) of months for which the 1-year rolling return is not below -5%. We aim at a Win5 score of at least 99%, so that for a maximum of only 1% of the months the rolling 1-year return is below -5%. We will use the term *"absolute return strategy"* when both the Win0 and the Win5 rates satisfy at least the 95% and 99% levels, respectively.

To determine the best model over the IS period (Dec 1970 – Dec 1992), we will consider the following parameter values for our N=12 universe:

1. The lookback length L= 3, 6, 9, 12 months (in the MOM(L) formula stated in eq. 1).
2. The degree of protection a = 0, 1, 2 (named low, medium and high protection, respectively).

[5] We thank Nathan Faber for providing the necessary calculations for deriving price data from yield data. Nathan proposed to work with monthly coupon payments. Following his methodology, we re-price a bond after one month, assume that it is sold, and roll over the proceeds along with the one month coupon payment into the new par bond. See also Faber (2015).

3. The number of best assets in the rotation, Top = 1, 2, 3, 4, 5, 6 (so no more than N/2 or 50% of the N=12 universe size).

Notice that most traditional models are governed by these parameter ranges. MOM (L) for L=9 months refers to the well-known SMA10 measure (a lookback of 9 months equals 10 prices) as used in the famous paper by Faber (2007). Our MOM(12) is similar in lookback length to the RET(L) measure with L=12M month lookback as used by Faber (2013) and Antonacci (2014). It also approaches the often used 1/3/6/12m average return filter (see above). Since our MOM(L) filter places its biggest weights on recent returns when L is small, the included MOM(L) for L=3 months will result in the highest turnover and the L=12 months in the lowest (and therefore the lowest transaction costs).

We did also limit the number of best assets (Top) to a maximum of 6 assets to stay close to the inheritance of Faber (2010, 2013) and others (like Asness, 2014) who used the best Top 33% (so Top=4 when N=12) assets in their rotational models. Keller (2014b) recommends Top=Sqrt(N) or N/2 which results in Top=3-6. We will here allow for higher Top numbers (up to Top=6, so N/2) since higher Top numbers imply more diversification and therefore lower variances, which is beneficial to our absolute return strategy.

The total number of IS scenarios considered are now 4 (lookback) * 3 (a) * 6 (Top) = 72 scenarios. We will search over all these 72 scenarios from the in-sample period (IS: 1971-1992) and use the best scenario to be tested over the out-of-sample period (OS: 1993-2015). But what does constitute the best? In view of the absolute return character of our strategy, we will mainly focus on scenarios with high Win5 scores, preferably 100%, so that the 1y-rolling-returns never come below the -5% boundary over the IS period. There are three scenarios which satisfy the Win5=100% criterion, see Fig. 3 (best values in **bold**). All three have L=12m lookback, a=2 (highest protection level) and Top>=4:

L	a	Top	R	V	D	Win0	Win5
12	2.0	4	**17.9%**	10.0%	10.9%	**96.8%**	**100.0%**
12	2.0	5	17.6%	9.7%	**10.4%**	**96.8%**	**100.0%**
12	2.0	6	17.1%	**9.2%**	**10.4%**	**96.8%**	**100.0%**

Fig. 3 The best IS scenarios (with Win5=100%)

Since the Top=6 scenario has the lowest volatility and drawdown (and probably the best diversification compared to Top<6), we choose this scenario as our best scenario on IS. As said, we aim at absolute returns so protection and diversification overrules performance. To that extend the best parameters are L=12m (long lookback, so less turnover), a=2 (high protection), Top=6 (most diversified). These parameter values also correspond to what we would expect intuitively for an absolute return strategy[6].

[6] When we switch the IS/OS period (optimizing now on 1992-2015), the best parameter values become L=12m, a=1, and Top=3, which gives a slightly more offensive strategy than our chosen PAA2 model, but with similar results. We prefer to use the earlier IS period, however, since it includes also rising rates, making it a more robust "learning" period. Notice that our split point (Dec 1992) is half way (22 years) our full sample (FS: Dec 1970-Dec 2015), while IS contains both rising (Dec 1970-Dec 1981) and falling (Dec 1981-Dec 1992) rates over a period of similar length (11 years each).

Notice that despite the very high (absolute return like) scores for Win0 and Win5 (97% respectively 100%), the CAGR (R) over IS still compounds to a high return of R=17.1% with low V and D readings (9.2% and 10.4%, respectively) which implies high SR and MAR values (1.05 and 1.64, respectively). We use a Sharpe Ratio based on excess return over the risk-free rate which is around 7.5% for IS and 2.5% for OS (5% over IS+OS).

We will call our best scenario (L=12m, Top=6) for a=2 the *high-protection PAA strategy*, PAA2 in short. In the next section we will also review the low and medium protection strategies PAA0 and PAA1 (with a=0 and a=1 respectively) with the same L=12m and Top=6.

To compare our new "protective" strategies with traditional dual momentum models, below we will also state the results for the dual momentum approach as proposed by Faber (called Aggressive GTAA, see Faber (2013) and Antonacci (2013b). However, for better comparison and to focus on the effect of our added protection, we will use the same SMA/Top6 approach as we did for our PAA strategies, and use the same data (our N12 universe) and costs[7].

4. Performance of the PAA scenario's: in-sample, out-of-sample, and full-sample

We will first start with some performance comparisons for the **in-sample period (IS: Dec 1970 – Dec 1992).** We will display the performance figures for PAA2 (the best scenario on IS with a=2, high protection) as well as for PAA1 (a=1, medium protection) and PAA0 (a=0, low protection). As our benchmark we will use the traditional static 60/40% portfolio with SPY/IEF for stock/bond. As stated above all results for the PAA family and Dual are with Top=6 and L=12m. We will judge the *absolute return* character of our strategies by Win0 (win-rate for 1-year-rolling-returns >= 0%) and Win5 (idem >= -5%) aiming for at least 95% and 99%, respectively.

IS	R	V	D	Win0	Win5	SR	MAR
PAA2	17.1%	**9.2%**	**10.4%**	**96.8%**	**100.0%**	**1.06**	**1.64**
PAA1	**17.4%**	9.8%	12.7%	95.7%	98.8%	1.02	1.37
PAA0	17.3%	10.3%	15.8%	94.5%	98.4%	0.96	1.09
Dual	17.3%	12.8%	25.4%	90.5%	96.0%	0.78	0.68
60/40	11.1%	11.2%	27.4%	80.2%	94.1%	0.33	0.40
SPY	11.8%	15.8%	42.6%	77.5%	85.4%	0.28	0.28

Fig. 4 The In-Sample (IS: Dec 1970 – Dec 1992) performance

As is shown in Fig. 4, the best return (R/CAGR=17.4%) is for a=1, i.e. the medium protective PAA1 model, which is slightly better than PAA0 and the traditional Dual momentum strategy (both R=17.3%). However, all risk measures like Volatility V, Max Drawdown D, Win0 and Win5 are best for PAA2. Notice too that these readings of PAA2 are better than the ones for PAA1, PAA0, Dual, 60/40 and finally SPY, in

[7] When using RET(12) instead of SMA(12) with PAA2 on FS (Dec 1970 – Dec 2015), the results were worse: R=13.4% (vs. 13.7% with SMA), V=9.6% (8.6%), D=18.1% (10.4%), Win0=93.4% (96.0%), Win5=96.4% (99.4%), with similar results in-sample (IS). Therefore we decided to use SMA also with Dual for a fair comparison of the effect of protective momentum.

a monotonic fashion. The same holds for the return/risk measures Sharp Ratio SR and MAR (=R/D) where our absolute return strategy PAA2 wins over all others, being three times the 60/40 SR and four times the 60/40 MAR.

Notice that the SR=1.06 of PAA2 is significant different from zero even when we use a haircut of 50% for data snooping (see Harvey, 2013)[8], since then its t-ratio equals t=2.46 which is highly significant (p<1%). But with such a high SR, a 0.25 haircut for data-snooping most likely would be enough, resulting in a t-ratio of 3.69 which is even better (p<0.025%). The PAA2 Sharpe Ratio SR is 0.73 higher than that of the 60/40 benchmark, which is also significant, even with a 25% haircut of SR to account for data-snooping (t=2.45).

Since our absolute return strategy should focus first on risk and only then on return, PAA2 fits the absolute return bill therefore handsomely. And although the three PAA strategies focus primary on risk, it is surprising that their returns R are so much better than those of the 60/40 benchmark and SPY (see also the equity graphs below). This is a demonstration of the first law in investing: “limit your losses”. Notice, however, that PAA2 is the result of in-sample optimization, so for IS data-snooping is in order (although we did not optimize for R).

Having declared PAA2 the best performing absolute return strategy on IS, we now need to assess its merit on our OS data set. Therefore, we turn to the **Out-of-Sample (OS: Dec 1992 –Dec 2015) performance** of our PAA models. The performance is shown in Fig. 5.

OS	R	V	D	Win0	Win5	SR	MAR
PAA2	10.5%	**7.9%**	8.8%	**95.3%**	98.9%	1.00	1.20
PAA1	11.3%	8.2%	**7.9%**	94.2%	**99.3%**	**1.06**	**1.43**
PAA0	11.6%	8.5%	8.3%	93.1%	98.2%	1.05	1.39
Dual	**12.5%**	10.2%	12.2%	92.4%	96.4%	0.97	1.02
60/40	8.4%	8.7%	29.5%	83.4%	89.5%	0.66	0.28
SPY	8.9%	14.5%	50.8%	80.5%	83.4%	0.44	0.18

Fig. 5 The Out-of-Sample (OS: Jan 1993 – Dec 2015) performance

Testing out-of-sample, the highest return is for Dual momentum (R=12.5%) with the low protection PAA0 (a=0) model on second place (R=11.6%). However, all risk and risk/return measures like V, D, Win0, Win5, SR, and MAR are better for the three PAA models than for Dual, 60/40 and SPY. Within the PAA family, PAA2 wins in terms of V and Win0, while PAA1 wins on D, Win5, SR and MAR. PAA0 only wins in terms of R, which is reasonable for a low protection strategy.

And again, the returns R of the PAA family (including the high protective one: PAA2) are all better than those of the 60/40 benchmark and SPY. However, the level of R (and the difference with 60/40) is less

[8] Harvey (2013) shows that to test the hypothesis SR=0 without data snooping, one can use the t-test with t=SR*sqrt(T) where T is in years and SR is the annualized Sharpe Ratio (over risk-free). When there is data snooping with less than 100 scenario’s (here 72), a haircut of 50% could be applied for SR around 0.5, or 25% if the SR is around 1 or higher. Recently, Paulsen (2016) proved that asymptotically (for large T) the haircut equals k/T for SR around 1, resulting in a haircut here as small as 14 percent when k=3 is the number of optimized parameters (Top, L, a) for PAA and T=22 year for IS. See also Harvey (2014).

than in-sample. Could this be the result of in-sample data snooping? We don't think so, since the risk-free rate over OS is also much lower than over IS (2.5% versus 7.5% per year for IS), while the return of SPY is also lower (8.9% per year compared to 11.8% for IS). This might explain the difference in levels of R of the PAA strategies out-of-sample with regard to those obtained in-sample.

The difference between the SR of PAA2 against that of the 60/40 benchmark equals 0.34, which is just significant (t=1.60, p=5%, one-tailed). Notice that we don't need a haircut since this is all out-of-sample (OS). The difference in SR with Dual is clearly insignificant.

With regard to our absolute return target, the high-protective PAA2 is the only model to satisfy our Win0 and Win5 requirements out-of-sample, given its 95% Win0 and (rounded) 99% Win5-rates. This also shows that the PAA2 model is superior as absolute return strategy to all the other models (including Dual, 60/40 and SPY) over the out-of-sample period. Also all the PAA strategies beat the other models in terms of the absolute-return characteristics Win0 and Win5.

When we combine IS and OS, we arrive at the full-sample (FS) period (Dec 1970 – Dec 2015). The performance measures for FS are (see Fig. 6):

FS	R	V	D	Win0	Win5	SR	MAR	P 2015
PAA2	13.7%	**8.6%**	**10.4%**	**96.0%**	**99.4%**	1.02	**1.32**	$ 32,213
PAA1	14.2%	9.1%	12.7%	94.9%	99.1%	**1.03**	1.12	$ 40,068
PAA0	14.3%	9.5%	15.8%	93.8%	98.3%	0.99	0.91	$ 41,332
Dual	**14.8%**	11.5%	25.4%	91.5%	96.2%	0.86	0.58	**$ 49,638**
60/40	9.7%	10.0%	29.5%	81.9%	91.7%	0.48	0.33	$ 6,414
SPY	10.3%	15.2%	50.8%	79.0%	84.3%	0.36	0.20	$ 8,361

Fig. 6 The Full-Sample (FS: Dec 1992 – Dec 2015) performance

As with OS, the best return (R=14.8%) over the full-sample (FS) is for the traditional Dual momentum model. Second comes again the low protective PAA0 strategy (R=14.3%), with PAA1 and PAA2 not far behind (R=14.2% and 13.7%, respectively). Although the PAA return is only 3-4% higher than that of the 60/40 benchmark and SPY, the final wealth (see the "P 2015" column, starting with $ 100 in Dec 1970) is an impressive 4-5 times bigger (and with much less risk). This again demonstrates the "limit your losses" adagio, which is the core of our protective momentum approach. Notice that the Dual strategy not only has the highest final wealth ($ 49,638) but also a twice as large drawdown (D=25.4%) as compared to the PAA2 and PAA1 strategy.

With respect to the risk measures (V, D, Win0, Win5), all PAA members are much better than the other models (Dual, the 60/40 benchmark and SPY). This holds true in particular for the max drawdown D for PAA2, which is up to five times better: 10% versus 25% (Dual), 30% (60/40) and 51% (SPY). Again, all risk measures deteriorate monotonically when going from the high protection PAA2 over PAA1 and PAA0 to Dual, the 60/40 benchmark and SPY. Also notice that over the full-sample PAA2 (and PAA1 rounded) satisfy the absolute return requirement with Win0 and Win5 (better than 95% and 99% respectively), where PAA0, Dual, 60/40 benchmark and SPY all fail to score up to mark.

Finally, the return/risk measures SR and MAR for PAA2 are over the full-sample also better than those of the 60/40 benchmark, SPY and even Dual. The Sharp Ratio of PAA2 (SR=1.02) is 2-3 times better than that of the benchmark and SPY, while the MAR measure (=R/D=1.32) is up to six times better than for 60/40 and SPY. The difference in SR between PAA2 and the 60/40 benchmark is 0.54, which is significant even when applying a 25% haircut for data-snooping on SR (t=2.53, see Harvey, 2013).

Below (**fig. 7 through 10**) we show the performance of our absolute return fund PAA2 over the Full-sample (FS = IS+OS) period compared to the 60/40 benchmark. Remember that results before 1993 (IS) are a result of in-sample optimization.

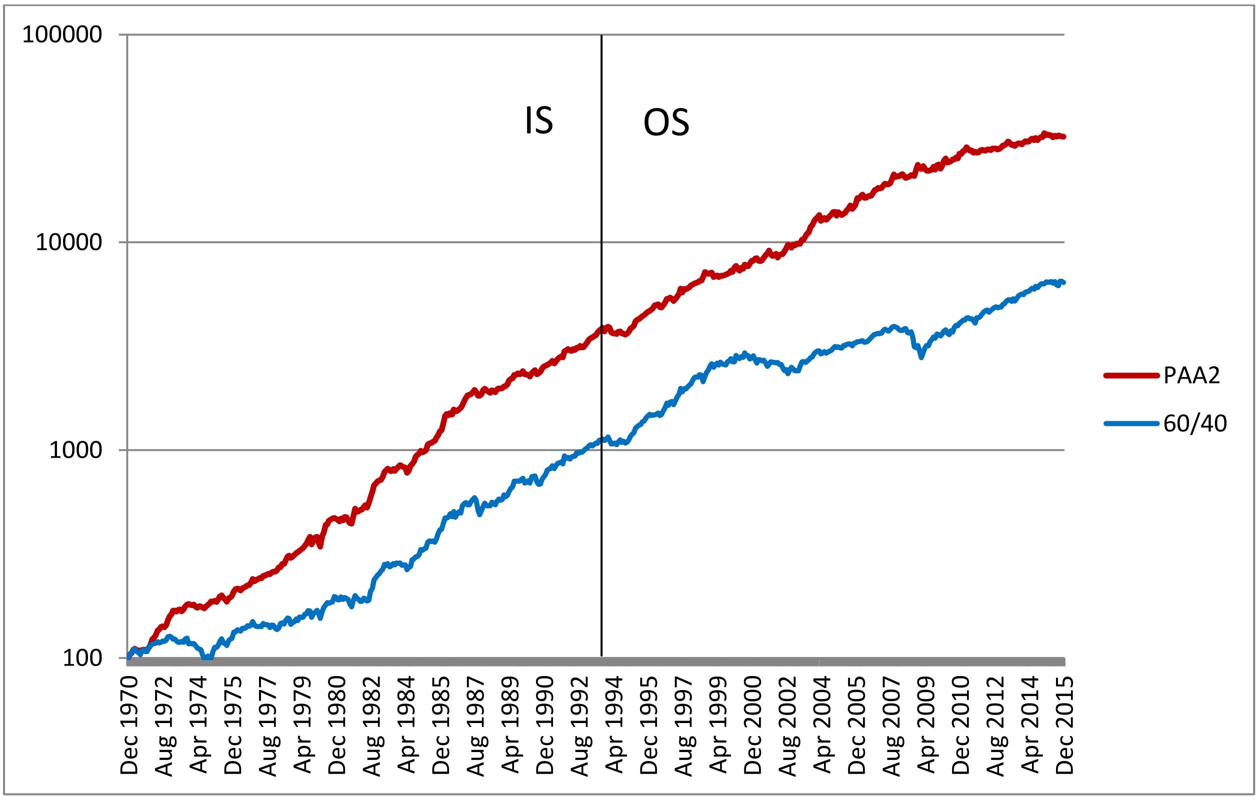

Fig. 7 The equity line for PAA2 and 60/40 (log scale, left=In-Sample, right=Out-of-Sample)

As we see from the equity line in Fig. 7 (log scale), the PAA2 curve is much less volatile than the 60/40 curve and with considerably less volatility and drawdowns while at the same time PAA2 shows much better performance than the 60/40 benchmark. This not only holds true for the in-sample period (IS: Dec 1970 – Dec 1992, including the rising-rates period Dec 1970 – Dec 1981), but also for the out-of-sample period (OS: Jan 1992 – Dec 2015).

In Fig. 8 we focus on drawdown, where the large (nearly 30%) drawdowns of the 60/40 benchmark contrast sharply with the constrained drawdowns (max around 10%, mostly less than 5%) of the PAA2 strategy. Notice that drawdowns not only have depth but also breadth. As can be seen from Fig. 8, for PAA2 the breadth (number of months in severe drawdown) is often (see e.g. 1994 and 2002) much less than that of 60/40. But to see the impact over say one year, one needs to look at the rolling returns.

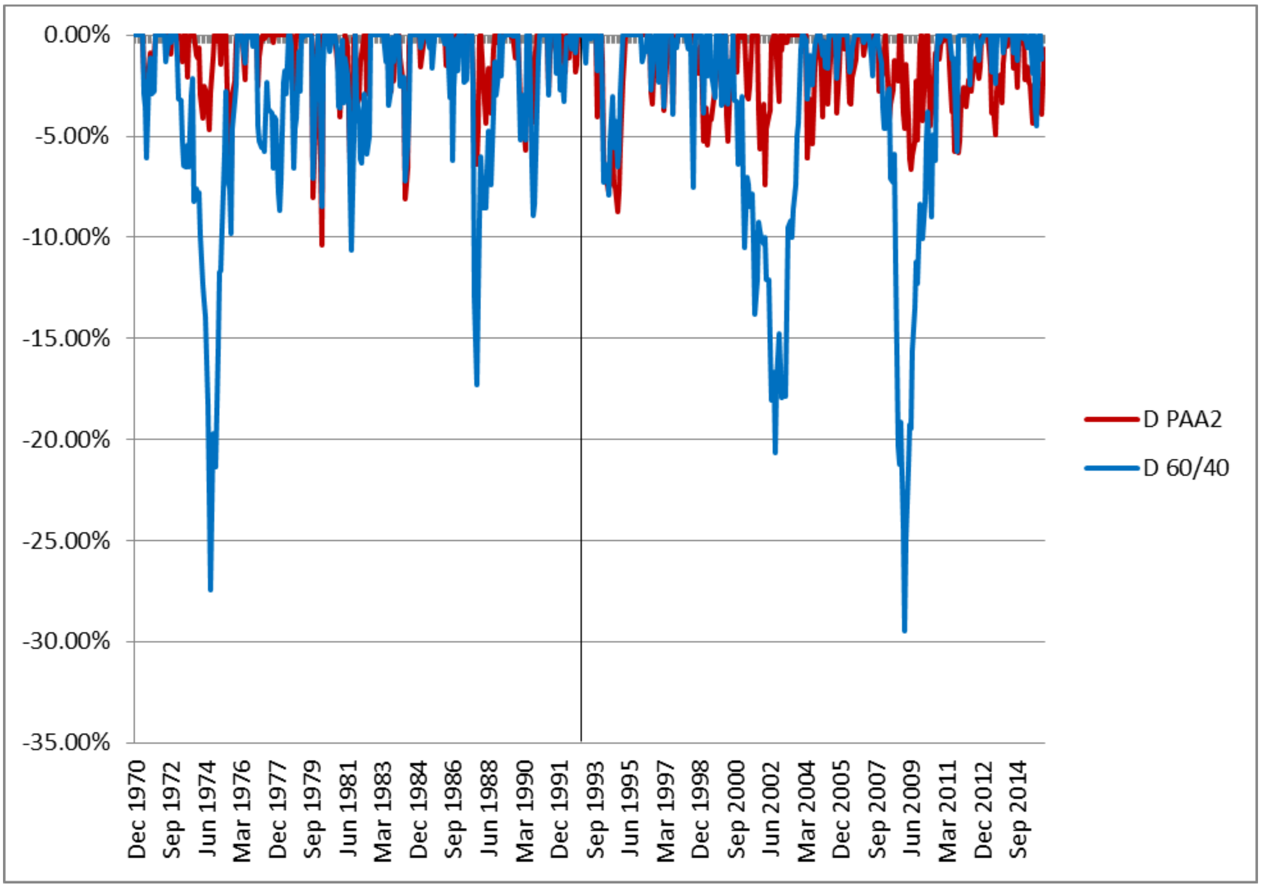

Fig. 8 The drawdown of PAA2 and 60/40

The 1-year-rolling-return in Fig. 9 shows that nearly all (96% according to Win0 in Fig. 6) of the 1-year-rolling-returns are non-negative. There is one clear exception, in 1994/1995, where the rolling 1-year return dips below the -5% watermark during three months (-6.3% in Oct 1994, -6.0% in Nov 1994 and -5.5% in Jan 1995), which corresponds to less than 1% of all 529 rolling 1y-returns (see Win5 in Fig. 6: 99.6% is at least -5% over the full-sample). Notice that the in-sample period Dec 1970 - Dec 1992 is better in terms of the Win0 and Win5 measure, which probably may be due to the applied optimization which brings the risk of data-snooping into play. However, even for the out-of-sample period the Win5 statistic is (rounded) 99%.

Notice that the performance of PAA2 is less than the 60/40 benchmark during the recent years. This is the price we pay for an absolute-return strategy: better in bear markets, less in bull markets. As said, the strategy pays out again in Jan 2016 when it made 3.3% (100% IEF) against 60/40 doing -1.7%.

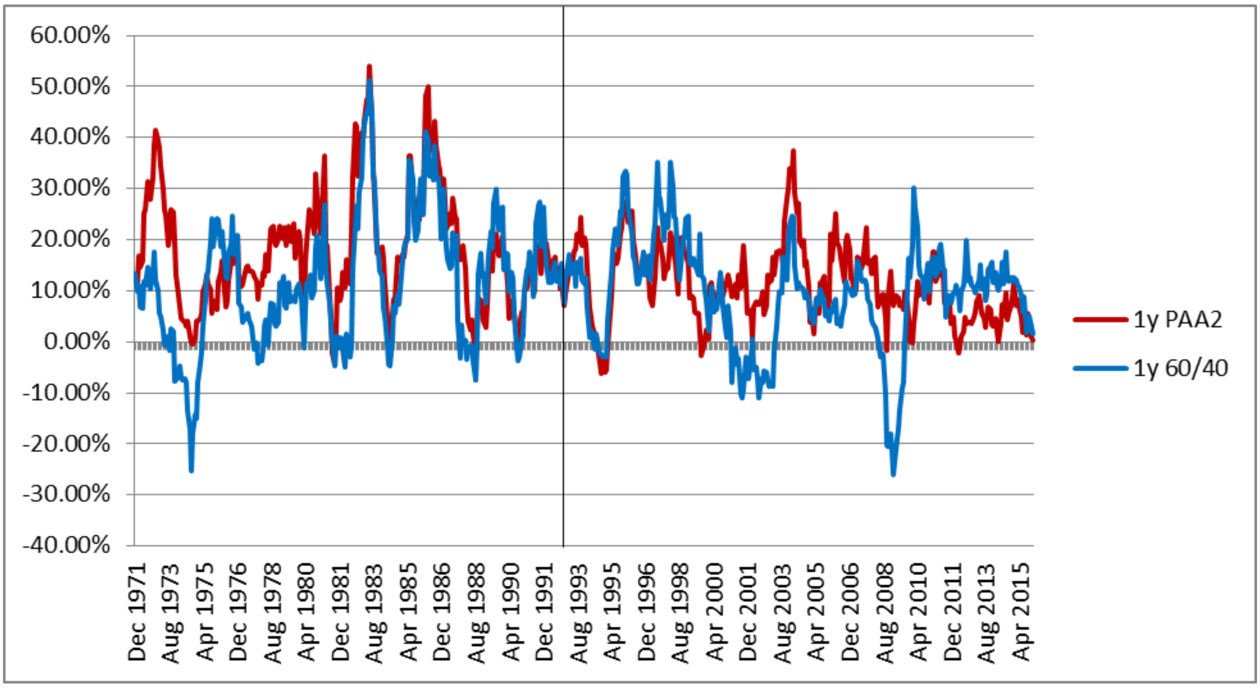

Fig. 9 The rolling 1-year return for PAA2 and 60/40

Fig. 10 shows the rolling 3-year return, which is easily always positive for PAA2, for both the in- and out-of- sample periods. From this (and the previous) graph it is clear that the average return of PAA2 is higher during the earlier in-sample (IS) period than the more recent out-of-sample (OS) period. Again, this might be due to a possible data-snooping effect although the return of the 60/40 benchmark is also substantially higher in-sample than out-of-sample (12.0% versus 8.5% per year, see Fig. 4 and 5). We also did not optimize in-sample on high returns, see section 3.

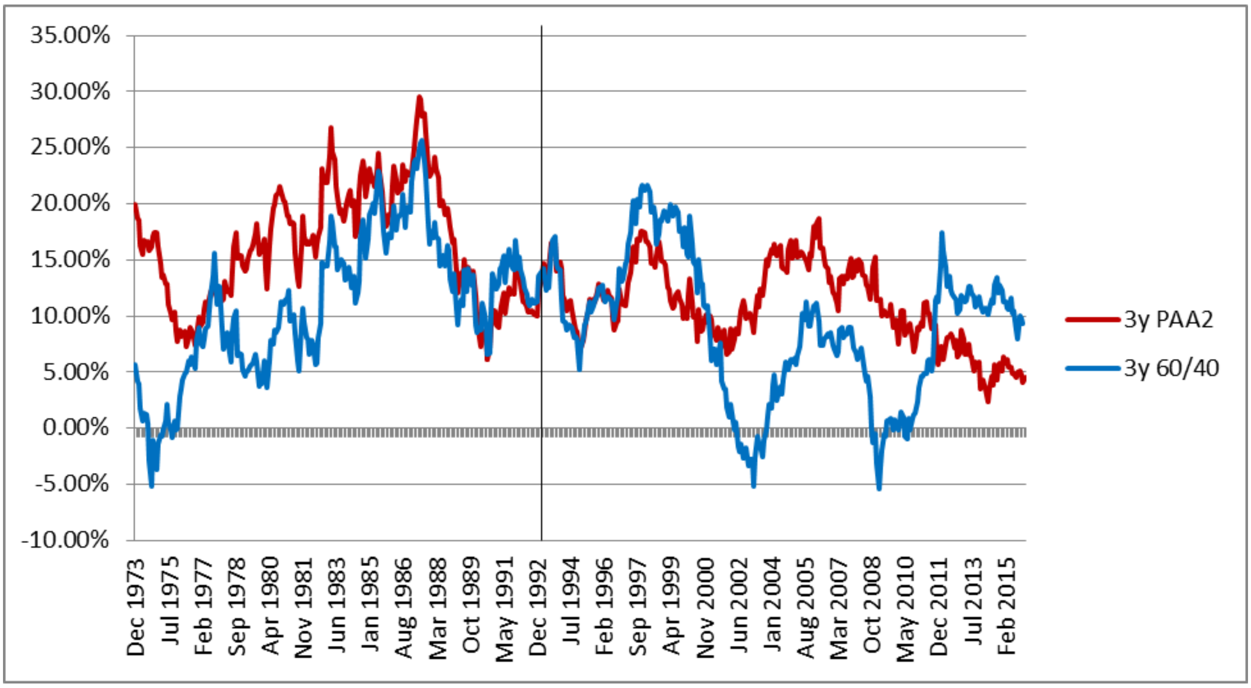

Fig. 10 The rolling-3y return of PAA2 and 60/40

Importantly, the risk-free (rf) rates (and 60/40 returns) were also very different: rf=7.5% for IS (with a R=17.1% for PAA2) versus rf=2.5% for OS (with R=10.5% for PAA2). In addition, it is also clear that during the most recent years, the PAA2 returns go from 10% to 5%, possibly as an effect of the Quantitative Easing (QE) of the Fed. However, during the recent 2015/2016 pull back, the PAA2 model proved its protective nature again by moving completely to bonds (IEF), which resulted in e.g. a +3.3% return in Jan 2016 for PAA2 (compared to a -1.7% return for 60/40). Finally, notice that even with heavy rate-hikes (as occurred during 1970–1981 when the risk-free rate went from 3% to 16%) the performance was well above the risk-free rate (average 15% for PAA2 compared to 7% for the risk-free rate in those 11 years).

Finally, we give the Bond Fraction (BF) over time (see Fig. 11), together with the (total return) equity curve for SPY (as a proxy for market health). The average bond fraction over Dec 1969 – Dec 2015 is 52.2%, so on average this is approximately a 50/50 (instead of a 60/40) strategy, but now with an active instead of a static bond/stock mix. Notice that the bond fraction (determined by the number of bad assets) follows the bear and bull markets surprisingly well and also recovers quickly (i.e. goes to less bonds) after the drawdowns (see e.g. 2003 and 2009).

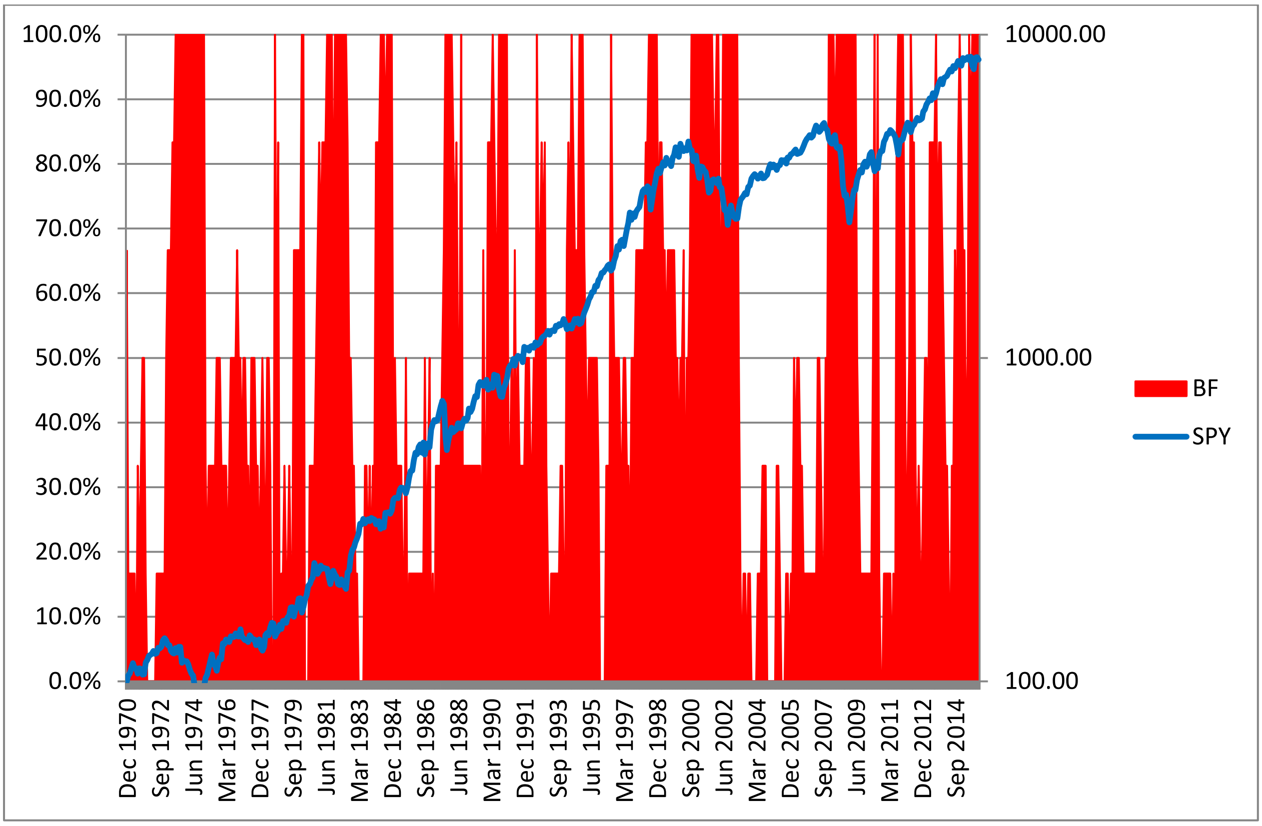

Fig. 11 Bond Fraction (BF, left axis) and SPY (right axis, log)

5. Better Safe than Sorry?

In the previous sections we used IEF as our "safe bond". Due to the hedgy character (negative correlation and beta of IEF with regard to SPY and other risky assets during bear markets), IEF performed well as "cash", even in periods of rising yields like the first decade (Dec 1970 – Dec 1981 to be precise). However, one might argue that the 7-10y maturity of IEF is still too long to be safe for times of rising rates, as is to be expected the coming years (2016-). Therefore we will look at some alternatives for IEF in this section.

As alternatives for IEF, using the various PAA models we examined all other bonds (BIL, SHV, SHY, IEI, TLT, AGG) in our ETF-proxy database on our in-sample period (Dec 1970 – Dec 1992). With regard to a single bond replacement, only SHY (1-3y) and BIL (1-3m) came close to IEF as "safe bond" for our PAA2 strategy in terms of return R and in particular the absolute-return characteristics Win0 and Win5. Both are also rather liquid, as is IEF. As said before (see Fig. 1), TLT is too volatile and has a longer maturity than IEF, while AGG turns out to be less hedgy than the treasuries IEF, SHY, etc.

We also looked at combinations of BIL, SHY and IEF where we chose each month the bond with the best momentum, based on MOM(12), irrespective of its sign (see also Nathan Faber, 2015). Using all three PAA (a=0,1,2) models on IS, only with the high-protective PAA2 we arrived at near absolute-return results (Win0>=95%, Win5>=99%). Below (see Fig. 12) we therefore present all combinations of IEF, SHY and BIL for PAA2 on IS:

IS	R	V	D	Win0	Win5	SR	MAR
PAA2 IEF	**17.1%**	9.2%	10.4%	96.8%	**100.0%**	1.06	1.64
PAA2 SHY	16.3%	7.1%	**7.4%**	**98.8%**	**100.0%**	**1.24**	2.21
PAA2 SHY/IEF	**17.1%**	7.9%	**7.4%**	98.4%	99.2%	**1.24**	**2.33**
PAA2 BIL	14.1%	**6.6%**	8.0%	**98.8%**	99.2%	1.03	1.76
PAA2 BIL/SHY	15.7%	6.9%	8.2%	**98.8%**	99.6%	1.20	1.92
PAA2 BIL/SHY/IEF	16.5%	7.7%	8.2%	97.6%	99.2%	1.20	2.01

Fig. 12 Results for various (combinations of) "safe bonds", in-sample (IS: Dec 1970 – Dec 1992,)

As can be seen from Fig. 12, only IEF and SHY satisfy the strong Win5=100% selection criterion we used before on IS, although all six strategies register a Win5 rate above 99%. Notice, however, that the SHY/IEF combination has the same high R as IEF, but with a better V, D, Win0, SR and MAR, while SHY (single) also scores very well on V, D, Win0, SR and MAR, with only a slightly lower R than that of IEF. And while the V and D of BIL and its combinations are also very good, return R is substantial lower for SHY than for IEF. Only the BIL/SHY/IEF combination comes close (R=16.5% vs. 17.1% for IEF), but loses against SHY/IEF on R, D, Win0, SR and MAR.

All the PAA2 models shown meet the absolute-return criteria (Win0>=95%, Win5>=99%). In view of the impressive R (equally high as IEF's), V (7.9% versus 9.2% for IEF) and in particular D (7.4% versus 10.4% for IEF) over IS, we prefer the SHY/IEF combination as the best alternative for our default safe bond choice IEF. Notice that both strategies (SHY/IEF and IEF) have the same R (17.1%) over IS while IEF has a better Win5 (100% compared to 99.2%) but a lower SR (1.06 compared to 1.24).

Below we present the Full Sample (FS: Dec 1970 – Dec 2015) results for all tested "safe bond" combinations:

FS	R	V	D	Win0	Win5	SR	MAR	P 2015
PAA2 IEF	**13.7%**	8.6%	10.4%	**96.0%**	99.4%	1.02	1.32	**$32,213**
PAA2 SHY	12.2%	6.8%	**8.2%**	94.9%	**99.6%**	**1.06**	**1.49**	$17,427
PAA2 SHY/IEF	13.1%	7.8%	9.3%	95.1%	**99.6%**	**1.06**	1.41	$25,948
PAA2 BIL	10.6%	**6.5%**	8.6%	94.5%	99.2%	0.87	1.23	$9,163
PAA2 BIL/SHY	11.8%	6.7%	**8.2%**	**95.1%**	99.4%	1.02	1.44	$14,851
PAA2 BIL/SHY/IEF	12.8%	7.7%	9.7%	94.5%	**99.6%**	1.03	1.32	$22,248

Fig. 13 Results for various (combinations of) "safe bonds", full-sample (IS: Dec 1970 – Dec 2015)

On FS, only IEF, SHY/IEF, and BIL/SHY (and SHY nearly) match our absolute-return criteria (Win0>=95%, Win5>=99%), while using SHY as safe bond gives the best MAR (1.49). With SHY/IEF the best SR (1.06) is reached. Of the four (near) absolute-return strategies only IEF (R=13.7%) and SHY/IEF (R=13.1%) have returns above 13% over FS, while BIL/SHY (R=11.8%) and SHY (12.2%) have lower returns.

In conclusion, we would suggest the SHY/IEF combination as the "safer bond" than our default bond IEF (as "cash" shelter in our PAA2 strategy). The SHY/IEF combination may show to be more resilient than IEF for rising rates in the future as it automatically switches to SHY (with a 1-3y duration) when IEF (7-10y) losses momentum over SHY. For investors with a stronger stomach, we still advise using IEF as safe bond in our highly protective strategy PAA2, since it also shows absolute returns (like SHY/IEF) while its return is potentially higher and its liquidity is very good.

6. Conclusions

In this paper we have shown that a very simple dual-momentum model when combined with vigorous crash protection results in a higher return and much lower risk than a traditional 60/40 stock/bond model. We call our strategy Protective Asset Allocation (PAA).

Using a simple SMA trend filter for both absolute and relative momentum and a risky universe of twelve global multi asset ETF-proxy funds, we did an In-Sample (IS: Dec 1970 – Dec 1992) and an-Out-of-Sample (OS: Jan 1993 – Dec 2015) backtest with the most protective PAA strategy (PAA2). The results can be characterized as a successful absolute-return strategy which can compete with a traditional 1-year term deposit, even in times of rate hikes. Here, we define "absolute-return" as a 1year-rolling-return which is not below 0% at least 95% of all months as well as 99% of time not below -5% (so Win0>=95% and Win5>=99%).

Applying a simple market-regime indicator based on the number of positive trending assets (the "multi-market breadth") to our risky universe, we move aggressively to 100% "safe" bonds in bad times and to 0% bonds in good times. Using IEF as safe bond, the resulting high-protective PAA2 strategy achieves the mentioned absolute-return targets, both on IS and OS, in contrast to the traditional dual-momentum strategy and our 60/40 benchmark. This makes PAA2 a successful absolute-return fund model in our opinion. Drawdown is limited to 10% while annual return (CAGR) is near 14% over the full-sample of 45 years.

In comparison, the fixed 60/40 stock/bond benchmark makes an annual return of 10% with a max drawdown of 30% and Win0/Win5 scores of only 82/92%. So we can improve risk and return/risk substantially over 60/40 (and dual momentum) by applying our "protective momentum" overlay based on multi-market breadth.

We also showed the effect of using other bond ETFs (like SHY) with less maturity than IEF (1-3y versus 7-10y) as "safe bond", including PAA2 models where the safe bond was chosen out of a combination (like SHY/IEF) based on momentum. They all beat the 60/40 benchmark and the traditional dual-momentum strategy on risk, return/risk and in most cases even on return characteristics. However, with the "protective momentum" strategies studied in this paper we focused primarily on "absolute-return" and risk above pure return.

Topics for future research are e.g. extending our asset allocation from the simple-dual momentum models used here to more general momentum models with volatility and correlation effects, like the FAA and EAA models of Keller (2012, 2014b). Also more advanced selections (including the effect of cross-sectional correlations) of one or more “safe” bonds from a separate bond universe (like explored in section 5) are on our list. Finally, our PAA strategy may be examined on more (small and large) universes, including country- and sector-universes.

Appendix A: Data construction

We try to find the best price proxies for 21 global ETFs from Dec 1969. All ETF proxy prices are monthly (EOM: end-of-month), adjusted for splits, dividends (aka total return), gross of taxes, net of fees, etc., similar to our ETF baselines.

We use the Yahoo Adjusted monthly (EOM) prices as baseline and minimize the tracking error (by changing the return weights) between the constructed price of the ETF proxy and this baseline for all (recent) years for which the baseline prices are available from Yahoo. Notice that all ETF proxies are also corrected this way for costs (fees, commissions, etc.) and dividends (incl. splits, etc.).

All sources are in Fig. A1. Most sources are free or affordable ($). All constructions/mixes (/) and concatenations (+) are in Fig. A2. Notice that monthly return weights in multi-asset mixes ("/" in Fig. A2) does not automatically add up to one because of dividend-, costs- and beta corrections.

Source	Weblink
Ibbotson SBBI Yearbook (Ibb)*	www.amazon.com/Stocks-Bonds-Bills-Inflation- Yearbook/dp/0979240220/ref=dp_ob_title_bk
Fama French (FF)	http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library/f-f_factors.html
Yahoo Finance	http://finance.yahoo.com/
MSCI	https://www.msci.com/end-of-day-data-search
REIT	https://www.reit.com/investing/index-data/monthly-index-values-returns
PremiumData ($)	http://www.premiumdata.net/products/datatools/spot.php
StockCharts ($)	http://www.stockcharts.com
ALFRED St. Louis FED	https://alfred.stlouisfed.org/release?rid=18
*) For HY we used ex Yearbook data from Andrei Simonov.	

Fig. A1 Data Sources ($: not free, but affordable)

Proxy	Mix (/) and Concat (+)	Ibbotson (Ibb)	Fama French (FF)	MSCI (Gross)	PremiumData (PD)	StockCharts (SC)	ALFRED	REIT	Yahoo Finance
SPY+	Ibb Large Cap + SPY	Large Cap (100%): 1969-1993							SPY (100%): 1993-2015
QQQ+	FF Tech + ^IXIC + ^NDX + QQQ		Tech (100%): 1969-1971						^IXIC (100.06%): 1971-1985 ^NDX (100.03%): 1985-1999 QQQ (100%): 1999-2015
IWM+	Ibb Small Cap + ^RUT +IWM	Small Cap (99.72%): 1969-1987							^RUT (100.11%): 1987-2000 IWM (100%): 2000-2015
VGK+	MSCI EUROPE + IEV +VGK			EUROPE (99.97%): 1969-2000					IEV (100.04%): 2000-2005 VGK (100%): 2005-2015
EWJ+	MSCI Japan + EWJ			Japan (99.96%): 1969-1996					EWJ (100%): 1996-2015
EEM+	MSCI Pacific ex Japan + MSCI EM + EEM			Pacific ex Japan (100%): 1969-1987 EM (99.92%): 1988-2003					EEM (100%): 2003-2015
EFA+	MSCI EAFA + EFA			EAFA (99.95%): 1969-2001					EFA (100%): 2001-2015
ACWX+	MSCI All World ex USA + ACWX			World ex US (99.83%): 1969-2008					ACWX (100%): 2008-2015
IYR+	FF Cnstr/RE/Fin Inv + REIT + IYR		Cnstr/RE/Fin (100.15%): 1969-1971					REIT (99.91%): 1972-2000	IYR (100%): 2000-2015
GSG+	GSCI spot + GSG (SC extended + Yahoo)				$GSCI (100%): 1969-1995	$GTX (100%): 1996-2006			GSG (100%): 2006-2015
GLD+	Gold spot + GLD				$GC (99.97%): 1969-2004				GLD (100%): 2004-2015
UUP+	US Dollar index + UUP				$DX (back filled, 99.90%): 1969 $DX (99.90%): 1970-2007				UUP (100%): 2007-2015
BIL+	Ibb T-Bill + DGS1MO + BIL	T-Bill (100%): 1969-2001					DGS1MO (100%): 2001-2007		BIL (100%): 2007-2015
SHV+	^IRX / DGS1 + SHV						DGS1 (15.9%): 1969-2007		^IRX (88.6%): 1969-2007 SHV (100%): 2007-2015
SHY+	DGS1 / DGS3 + SHY						DGS1 (55.1%): 1969-2002 DGS3 (53.3%): 1969-2002		SHY (100%): 2002-2015
IEI+	DGS3 / DGS7 + IEI						DGS3 (19.4%): 1969-2007 DGS7 (86.4%): 1969-2007		IEI (100%): 2007-2015
IEF+	^TNX + IEF								^TNX (106%): 1969-2002 IEF (100%): 2002-2015
TLT+	Ibb LT Treasury Bond + TLT	LT T-Bond (93.6%): 1969-2002							TLT (100%): 2002-2015
HYG+	Ibb High Yield + FAHYX + HYG	High Yield (90.5%): 1969-2005							FAHYX (99.95%): 2006-2007 HYG (100%): 2007-2015
LQD+	Ibb Corp Bond + LQD	Corp Bond (97.9%): 1969-2002							LQD (100%): 2002-2015
AGG+	DGS3 / Ibb LT T-Bond + AGG	LT T-Bond (44.0%): 1969-2003					DGS3 (51.5%): 1969-2003		AGG (100%): 2003-2015

Fig. A2 Construction of ETF proxy data Dec 1969 - Dec 2015 (mixes / and concatenations +)

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