Original Article

The value of stop-loss, stop-gain strategies in dynamic asset allocation

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Austin Shelton

is a Finance Ph.D student at Florida Atlantic University in Boca Raton, Florida. He holds a MS and BS in Finance from The University of Arizona. Prior to the Ph.D program, he worked as a Data Scientist at Dun & Bradstreet Credibility Corp. in Malibu, California and prior to earning his MS worked as a Brokerage Associate at the Vanguard Group in Scottsdale, Arizona.

Correspondence: Austin Shelton, Department of Finance, Florida Atlantic University, 777 Glades Rd, Boca Raton, FL 33431, USA
E-mail: ashelton2015@fau.edu

ABSTRACT Dynamic asset allocation strategies which utilize stop-loss and stop-gain rules may dramatically decrease risk and even increase long-term return relative to other traditional asset allocation strategies. I introduce a dynamic asset allocation strategy which shifts portfolio weights based on predefined stop-loss and stop-gain rules. The two-asset (S&P mutual fund and bond mutual fund) strategy tested from 1990 to 2012 produces an annual geometric return of 8.45% vs. 7.50% for the underlying S&P 500 Index fund with 50% less volatility (9.41% vs. 18.76% for the S&P index fund). In addition, the strategy displays a positive and significant CAPM alpha over the sample period. The strategy's very strong results are robust to changes in the user-specified parameters, such as the level and number of stop placements. All findings indicate that portfolio stop-loss and stop-gain rule-based strategies comprise a promising dynamic asset allocation approach deserving of further research and development.

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INTRODUCTION AND MOTIVATION

Stop-losses and stop-gains have not traditionally been considered as part of an asset allocation methodology. Instead, modern portfolio theory has been driven by mean–variance optimization since Harry Markowitz revolutionized modern finance (Markowitz, 1952). Sophisticated investors are rightfully focused on maximizing their return per-unit risk by investing along the efficient frontier. Of course, the practical problem is that asset returns are not easily, if even at all, predictable (Ferson *et al*, 2003). In addition, Markowitz' model and most asset allocation models assume a static single-period framework.

Thus, I design and introduce an alternative method of asset allocation to be used between major asset groups. My alternative methodology is based on the placement of stop-losses and stop-gains set by predefined rules. The implicit goal of my method is to maximize return per-unit risk. However, there is zero prediction of any return moment within my methodology. Instead, I use stop-loss and stop-gain rules alone to shift asset allocations. Thus, no inferences regarding expected return are made and no optimization of any sort is performed within my methodology.

Since my strategy is naturally dynamic in nature and therefore can be classified as a tactical or dynamic asset allocation strategy, a brief review of the history of dynamic asset allocation and risk management strategies, especially those involving stop-losses and risk management rules, is quite helpful.

Dybvig (1988) shows that stop-losses tend to be wealth destroying assuming that the underlying asset can either go up or down next period with equal probability and magnitude. This is because when triggered a stop-loss has a positive cost associated with it due to the bid-ask spread and commissions. While sensible, this result relates to market microstructure issues rather than using stop-losses within a long-term dynamic asset allocation framework as done in this paper.

Perold and Sharpe (1988) authored the defining work which started the discussion of dynamic asset allocation strategies. Perold and Sharpe identify four major types of dynamic asset allocation strategies: (1) buy-and-hold, (2) portfolio insurance, (3) constant mix, and (4) option-based portfolio insurance. Of course, buy-and-hold is essentially just a passive strategy in which an investor simply buys a certain percentage of stocks, bonds, and/or other assets and holds them until he wishes to liquidate his holdings. In a constant mix strategy, an investor keeps his weightings of all assets constant over time. Therefore, the investor sells stocks as they rise and buys them as they fall in order to keep the proportion of equity holdings in his portfolio constant. In portfolio insurance-type strategies, an investor does the opposite of a constant mix strategy to hedge against market collapses. That is, the investor sells stocks as they fall to cut his losses and buys them as they rise. Perold and Sharpe show the rather intuitive result that the type of market dictates which strategy is most effective and therefore no strategy is dominant across all market states. For example, portfolio insurance strategies do better than constant mix strategies in bear markets but will, of course, do this at the expense of underperforming constant mix strategies in bull markets.

Herold *et al* (2007) show that a risk-based portfolio strategy that controls for portfolio shortfall risk enhances long-run performance. In their dynamic framework, investors have the best risk-adjusted performance and lowest portfolio shortfalls by allocating higher proportions to stocks initially and then shifting to a more conservative strategy over time. Although their approach does not involve stop-losses, their intuition of reducing portfolio shortfalls and reducing portfolio risk is somewhat similar to my own. Their approach has important real-world implications as it is consistent with the ensuing development and popularity of life-cycle mutual funds which decrease an investor's allocation to equities and increase his allocation to bonds as he nears retirement.

Clarke *et al* (2006) show the strong performance of a minimum variance portfolio of US stocks over 456 months of historical data. A portfolio in which stocks are selected via an algorithm which minimizes portfolio variance with no regard to expected return posts a Sharpe Ratio of over .5 over the period versus .36 for the market portfolio. This suggests that even when expected returns are not considered, minimizing the risk of one's portfolio tends to add to risk-adjusted return.

In a recent work, Hocquard *et al* (2015) introduce a dynamic asset allocation strategy in which investors allocate funds between the stock market and a risk-free asset to target a left-truncated Gaussian distribution with an exogenous volatility parameter. They show the strategy has strong results in simulation relative to the S&P 500 across varying specifications of the targeted volatility parameter, especially in risk-adjusted terms. While their results are impressive, they also show that their strategy does not consistently outperform a very simplistic stop-loss based strategy in risk-adjusted terms and suffers from higher trading costs than such a strategy.

Most notably, Kaminski and Lo (2007) develop a strategy in which one invests entirely in equities until stop-losses are hit and then shifts entirely to long-term government bonds for set periods of time. They find their system has a significant CAPM alpha and a historical tendency to allocate to bonds preceding large equity market downturns, providing a logical basis for asset allocation methodologies which incorporate stop-losses.

My marginal contribution to the relevant literature is multiple. First, I implement a dynamic asset allocation strategy that utilizes a series of stop-losses and stop-gains rather than just stop-losses alone. No major study I am aware of to date does this. This naturally cuts the return distribution of the strategy further from 'left-truncated Gaussian' to just 'truncated Gaussian.' It also defeats the claim that the strategy is simply a synthetic form of portfolio insurance. In my view, it may be that capturing gains is just as important as cutting losses, and therefore, stop-gains should be considered within an asset allocation paradigm in addition to stop-losses.

Next, the portfolio reallocations are designed to be modest within my model (a movement from 40% stocks and 60% bonds to 46% stocks and 54% bonds would be a typical change, instead of a 100% move from stocks to bonds tested in Lo and Kaminski in most other studies). As such, my strategy or a variant of it has great potential to actually be implemented by many portfolio managers.

Another unique separating factor of my model is that stops are incorporated within one's bond portfolio, rather than just fixing investment in bonds (or a risk-free asset) for arbitrary periods of time after equity stops are triggered. Finally, stop-losses and stop-gains are normalized throughout time based on lagged-return volatility within my model and my model is completely generalizable to a portfolio with any number of investment assets.

Most importantly though, I show that a stop-loss and stop-gain-based strategy is likely to actually be the dominant risk-adjusted strategy, when the prior literature informs us that no strategy is likely to dominate and therefore be a replacement for "buy-and-hold" over the long run (Perold and Sharpe, 1988). As Perold and Sharpe argue, it is clear that no particular dynamic asset allocation strategy will dominate in all markets, be they "bull," "bear," or "flat." However, I argue that the performance of an asset allocation strategy in particular market states should not be one's focus, but rather the expectation of the strategy's performance over the long run, which naturally contains many potential market states. I show using Monte Carlo simulation that whether or not we introduce jumps ('crisis' years in my methodology) into markets, and even if we simulate markets *as less volatile* than observed historically a stop-loss, stop-gain-based strategy produces a much higher information ratio than a typical "buy-and-hold" (S&P 500) or constant mix (balanced 70–30 index) investment strategy. For any unfamiliar readers, the 'information ratio' is calculated as the asset's mean return over volatility following Goodwin (1998). Thus, my findings strongly suggest that the risk-adjusted return of a dynamic asset allocation strategy which constricts both gains and losses dominates the risk-adjusted return of other commonly used asset allocation strategies.

Finally, I explain why my strategy has historically outperformed. I show that the time-varying correlation structure of stocks and bonds seems to be a major driving factor of the performance of my strategy. This understanding of why the stop-loss, stop-gain asset allocation strategy outperforms is perhaps more important than the finding that it does.

In totality, I develop a new class of dynamic asset allocation strategies which truncate one's possible returns through the placement of both stop-losses and stop-gains on all assets held. Although somewhat similar in intuition to portfolio insurance since one wishes to hedge against downturns in both strategies, my strategy is distinct and unique with a different risk and return profile than portfolio insurance.

Intuitively, I was motivated to test the methodology for three reasons. First, since stock returns are far from easily predictable, it is sensible to consider an asset allocation strategy which only targets the minimization of risk rather than the accurate prediction of future return and minimization of risk. Second, the use of both stop-losses and stop-gains on one's portfolio composed of stocks and bonds should naturally rebalance towards the asset with the higher expected return if (1) assets have non-constant correlations which diverge in financial crises, (2) equities have a positive serial correlation over the short term, and (3) equities exhibit long-term mean reversion. Of course, there is evidence that all these conditions may hold (Conrad and Kaul, 1988; De Bondt and Thaler, 1987; Fama and French, 1988; Gulko, 2002; Jegadeesh, 1990; Jegadeesh and Titman, 1993; Poterba and Summers, 1988).

As far as the time-varying correlation structure of major asset groups, it has been noted that during periods of large decline in one major asset group (stocks) there is often a 'flight to safety' in which investor funds flow to the less risky major asset group (bonds) (Gulko, 2002). During and after the 2008 financial crisis, this 'decoupling' effect originally noted by Gulko (2002) was widely commented on as the 'flight to safety' or 'flight to quality' by the financial media (Noeth and Sengupta, 2010).

Essentially, 'decoupling' is the tendency for the correlation between the US stock market and US treasury bonds and high-grade corporates to diverge during financial crises. Of course, the 'flight to safety' by investors who demand safer and highly liquid assets during volatile markets is what drives up the return of government and investment-grade bonds and causes the 'decoupling' effect during large market downturns. Since, 'decoupling' is easily observable empirically, one should expect a strategy which utilizes stop-loss and stop-gain rules to shift allocations between an equity and a bond fund to take advantage of liquidity shocks and the ensuing 'flight to safety' observed during a financial crisis. That is, when stop-losses on equities are triggered during a significant market downturn, the portfolio allocation to bonds is naturally increased by such rules. At just this point in time, the correlation between stocks and bonds is often highly negative, and the expected return of bonds relative to stocks has increased. For this reason, we should observe that asset allocation strategies between equities and bonds which incorporate stop-loss and stop-gain rules greatly outperform balanced funds ("constant mix") or straight investment in equities ("buy-and-hold") during financial crises' and market downturns.

Finally, stop-losses naturally provide value in the presence of momentum as one often is 'stopped-out' before equities endure prolonged periods of significant downturn. Since momentum of individual firm returns and aggregate market returns at the monthly level are both well documented, it is only natural to design an asset allocation strategy which may capture at least a portion of the 'momentum alpha' while simultaneously decreasing portfolio variance. Kaminski and Lo (2007) prove a very intuitive fact along these lines well worth proving formally: a portfolio composed of solely a risk-free asset and a risky asset that has a normally distributed return and positive return serial correlation earns a positive excess return by the use of stop-losses on the risky asset.

Due to the non-constant correlation structure of major asset groups, the relatively low amount of predictability in individual asset returns, momentum in equity returns over short horizons, and long-term mean reversion or reversal in equity returns, it is worthwhile to reconsider dynamic asset allocation strategies that incorporate both stop-loss and stop-gain rules. In this work, I argue that such strategies may have a place in investors' portfolios and should further be explored as a new class of dynamic asset allocation strategy.

ASSET ALLOCATION STOP-LOSS, STOP-GAIN STRATEGY

The asset allocation strategy I develop is relatively simplistic. Within my strategy, an investor holds a portfolio of N different investment assets, which are predetermined before the start of investment. For the sake of simplicity, and because many investors are primarily concerned with their portfolio allocations to stocks and bonds, I set N equal to 2 throughout. In order to closely match the investments of many institutional portfolio managers and retail investors alike, the two investments I consider in this paper are a large S&P 500 index mutual fund and a large investment-grade bond mutual fund. Still, this strategy is easily extendible to any number of investment assets.

After an investor determines the assets he wishes to hold within his portfolio, he must determine the number of stop-losses (which I will denote I), the number of stop-gains (which I will denote J), and fixed spread between both stop-losses and stop-gains (which I will denote Z) that he wishes to place on his portfolio. Since there are $I * J$ unique stop-loss, stop-gain combinations, the investor holds $I * J$ positions within his portfolio. At any point in time, each position is composed of only one of the N possible investment assets. For each position, the stop-loss and stop-gain level is multiplied by the 6-month lagged annualized return volatility of the asset currently held to determine the stop-loss and stop-gain level on the position at that point in time.

Now, for clarity, let me give an example. Let us assume we want to pick two investment assets to hold within our portfolio: an S&P 500 mutual fund and an investment-grade bond mutual fund ($N = 2$). Let us also assume we choose I to be 4, J to be 4, and Z to be .5. That means we set up $I * J = 16$ positions, each with a unique stop-loss, stop-gain combination. The stop-loss and stop-gain levels on the positions in this example are shown in Table 1.

In total in this example, we have 16 positions with stop-loss and stop-gain levels of .5, 1, 1.5, and 2. Mathematically, the exact stop-levels and numbering of an investor's positions is written below:

$$\text{For } i = 1, \ldots, I \quad \& \quad j = 1, \ldots, J$$
$$\alpha_k = i * Z \quad \& \quad \beta_k = j * Z,$$
$$\delta_k = (\alpha_k, \beta_k).$$

The k positions are numbered so that $k = (j - 1) * J + i$. $\delta_k = (\alpha_k, \beta_k)$ is a vector containing the unique stop-loss level, i, and stop-gain level, j, of position k.

After an investor determines the assets he wishes to hold within his portfolio and I, J,

Table 1: Stop-loss and stop-gain levels when $I = 4$, $J = 4$, and $Z = .5$

Position	*Stop-loss level*	*Stop-gain level*
1	0.5	0.5
2	1	0.5
3	1.5	0.5
4	2	0.5
5	0.5	1
6	1	1
7	1.5	1
8	2	1
9	0.5	1.5
10	1	1.5
11	1.5	1.5
12	2	1.5
13	0.5	2
14	1	2
15	1.5	2
16	2	2

Note: For all positions, the stop-loss and stop-gain levels are multiples of the 6-month lagged (annualized) volatility of the asset currently held.

and Z, he may begin investment. On day 1, he invests $\frac{1}{N}$ of his capital in each of the N assets he chooses. Thus, in our example, with an S&P mutual fund and long-term investment-grade bond fund as our portfolio assets, we originally invest 50% of our capital in the S&P mutual fund and 50% in the bond mutual fund. Since we have 16 positions we hold at any point in time within this specification of the strategy, we originally invest 8 positions in the S&P mutual fund and 8 positions in the bond mutual fund.

After investment, it is straightforward to follow the rules of the stop-loss, stop-gain strategy to determine the investor's asset allocation at any point in time. For each of the $I * J$ positions, on each day, if the holding period return of the asset currently held is less than or equal to the stop-loss level set on the position or greater than or equal to the stop-gain level set on the position, then one trades from the asset currently held to another of the $(N-1)$ available assets. If N is greater than 2, than one simply picks another of the N assets at random (with each of the remaining assets having probability of $\frac{1}{N-1}$ of being drawn). In the 2-asset case, one simply trades to the other asset. In addition, when a stop-loss or stop-gain is triggered on any position, one reweights his entire portfolio so that all positions are equal-weighted. This process is repeated going forward at any point at which a stop-loss or stop-gain is hit. Thus, an investor can easily continue to follow the strategy for an indefinite amount of time. Mathematically, the rules of the strategy in the N-asset case are written and explained below:

(1) $\forall\, k \text{ let} f\left(x_{k,t}\right) = \begin{cases} 1 & \text{if } R_{k,t} \le \alpha_k \quad \text{or} \quad R_{k,t} \ge \beta_k \\ 0 \; o.w. \end{cases}$, where $x_{k,t}$ represents the asset held as the k_{th} position at time t, $f\left(x_{k,t}\right)$ is a function which takes a value of '1' if a stop was triggered on the k_{th} position at time t and a value of '0' otherwise, and $R_{k,t}$ is the holding period return of the asset being held as the k_{th} position at time t. The binary function simply signals whether a stop-loss or stop-gain level was met or exceeded for all K portfolios at time t. Of course, t is initially set to 1.

(2) $\forall k \in K$ if $f\left(x_{k,t}\right) = 1$, then a trade is placed on the k_{th} position at time $t+1$ such that the $p(x_{k,t+1} = \{1, 2, 3, \{x_{k,t}\}, \ldots, N\}) = \frac{1}{N-1}$. That is, for each of the portfolios in which a stop was triggered at time t trade into a new asset (with equal, random probability of choosing any new asset) at time $t+1$.

(3) Let $w_{k,t+1} = \frac{1}{K}\, \mathit{if} \sum_{k=1}^{K} f\left(x_{k,t}\right) \ge 1$. Equally weight all K portfolios at time $t+1$ if one or more stops were triggered at time t.

(4) Repeat steps (1) through (3) for $t = t + 1$.

The strategy has interesting implications in both the 2-asset and more complex N-asset case. However, due to the 'decoupling' effect observed between equities and bonds during market crises, I am most interested in the performance of my strategy in a 2-asset case where the investment assets are an equity index mutual fund and a bond index mutual fund. In addition, since most investors allocate the majority of their financial investments to diversified equity and bond funds, this becomes the most natural place to start testing the strategy from an applied portfolio management perspective.

DATA

As data for this study, I use historical daily Net Asset Values (NAVs) and dividend yields for the dates from January 2, 1990 to Dec 31, 2012 for two large Vanguard mutual funds: VFINX, the Vanguard 500 Index Fund, and VWESX, the Vanguard Long-Term Investment-Grade bond fund. I gathered the data for both funds directly from Vanguard's investor website. These data are also publicly available from Yahoo! Finance as well as other online sources. In addition, I use Ken

French's data from his website for historical Fama–French Carhart factors, as well as historical estimation of the market return and the risk-free rate over the period considered.

Returns on the Vanguard funds were calculated from daily NAVs and dividend yields assuming that all dividends paid by either fund were paid at month end and reinvested. Altogether, the data encompass 5800 daily NAV observations for each of the mutual funds. Since stop-loss and stop-gain rules in my model are multiples of the rolling 6-month annualized standard deviation of return of each of the underlying funds, only the 127th (July 3, 1990) through 5800th (Dec 31, 2012) observations encompass the period of allowable testing for the asset allocation strategy.

There were several reasons for choosing two Vanguard index mutual funds as the two assets to represent a broad stock index and broad bond index within my asset allocation strategy. First, Vanguard offers index funds at very low management fees and is considered the world's premium provider of index funds. It is obviously much less costly for a typical investor to buy the Vanguard 500 Index Fund than to buy the 500 companies in the S&P 500 and rebalance the portfolio on the investor's own as a large index fund can achieve large economies of scale. Second, both funds are very large, reputable, and efficient funds commonly held by retail and institutional investors alike. Finally, and most importantly, by using mutual funds it is realistic instead of problematic to gather only one potential stop "price" per day, the fund's Net Asset Value (NAV). Thus, when a stop-loss or stop-gain is triggered based on a fund's closing NAV, an exchange occurs at the next day's (T + 1) NAV from VWESX to VFINX or vice versa (for example, one would receive the NAV calculated after today's market close for a stop triggered by yesterday's closing NAV). This is a perfectly realistic assumption without taking into account commissions, since mutual funds are only exchanged at one price per day, their NAV. Thus, my strategy was actually tradable over the dataset considered as it is guaranteed that one would be able to exchange between the two mutual funds at their reported NAVs. This same condition is *not* guaranteed when one uses the returns of the underlying index such as the S&P 500, individual stocks, or closed-end funds including exchange traded funds (ETFs) as one may not have been able to sell shares on the open market at the daily closing price listed in a dataset such as CRSP.

In addition, as individual stocks and exchange traded funds would be continuously traded throughout the market day, microstructure issues such as slippage from the bid-ask spread and commissions could and to some extent would decrease the actual net return of the strategy through such vehicles. However, such microstructure issues are completely avoided through the use of open-end fund returns. While when many financial experts think stop-losses they think microstructure, this paper is meant to encourage new methodologies in dynamic asset allocation which involve stop-loss and stop-gain rules.

Of course, the costs of holding a diversified portfolio, including incurring bid-ask spreads and commissions to buy and sell positions and rebalance one's portfolio as well as a very modest management fee, are already encapsulated in the Vanguard NAVs. But, Vanguard, similar to other large mutual fund companies has oftentimes allowed investors to exchange between these no-load funds free of charge. So, I would argue returns reported already are net of trading costs as they include the embedded bid-ask spread, commissions, and management fees from holding and exchanging the product. Taxes, of course, are not estimated, but I would note that many retail investors may wish to implement such strategies in nontaxable accounts such as an IRA and therefore may find the strategy very appealing.

The standard asset allocation stop-loss, stop-gain strategy I test is a specification in which $I = 4$, $J = 4$, and $Z = .5$. Asset 1 is the Vanguard 500 Index Fund (VFINX), and asset 2 is the Vanguard Long-Term Government Bond Index Fund (VWESX). Thus, since $I * J = 16$, 8 positions are invested initially in VFINX and 8 into VWESX on July 2, 1990 in this baseline specification. Then, as stop-losses and stop-gains are triggered on any of the 16 positions held on days 127 (July 3, 1990) to 5800 (December 31, 2012), those positions are exchanged into VWESX from VFINX or vice versa and all 16 positions are rebalanced.

RESULTS

The baseline specification above produces an annual geometric return of 8.45% over the 23-year period considered, with an annualized standard deviation of only 9.41% (all statistics reported use daily returns to estimate return volatility). In comparison, VFINX, the Vanguard S&P 500 Index Fund, produced a lower 7.50% annual geometric return, with an annualized standard deviation of 18.76% over the period. The comparison of returns to VFINX is important as VFINX represents the most basic "buy-and-hold" asset allocation strategy, that is, to hold an S&P 500 index fund as it is a proxy for the overall market. A 70–30 balanced portfolio of VFINX and VWESX produced a 7.16% annual geometric return, with an annualized standard deviation of 12.98% over the period. This 70–30 balanced portfolio is important for comparison relative to the strategy as it represents a typical, basic "constant mix" asset allocation strategy. Finally, VWESX produced a 4.57% annual geometric return, with an annualized standard deviation of 8.92%. Again, this can be viewed as another very basic and conservative "buy-and-hold" investment strategy, in which one holds a proxy for the aggregate long-term investment-grade bond market instead of the aggregate stock market. The stop-loss, stop-gain strategy with the baseline specification was dominant from a return prospective as it provided both superior risk-adjusted return and higher raw return than VFINX, VWESX, or any balanced index ("constant mix" strategy) of the two.

The baseline asset allocation strategy noticeably outperforms all other tested portfolios. It has a higher geometric return than VFINX, VWESX, or the balanced index. The asset allocation strategy also has 50% lower volatility than VFINX and a 27.5% lower return volatility than the balanced index. In fact, the bond fund, VWESX, has only a marginally lower standard deviation of return than the asset allocation strategy (5.2% lower) which is quite amazing. This is also suggestive of the fact that the strategy must have a higher historical allocation to bonds when correlations between stocks and bonds are most negative. In terms of reward per-unit risk as measured by the Information Ratio, the base allocation strategy far outperforms either of the underlying index funds ("buy-and-hold") or the balanced strategy ("constant mix") with its Information Ratio of .90. Table 2 below details the annualized geometric return, arithmetic return, standard deviation, and Informatiom Ratio of the Asset Allocation stop-loss, stop-gain strategy, VFINX, VWESX, and a 70–30 balanced index of VFINX and VWESX from 1990–2012.

Perhaps the greatest potential benefit of stop-loss and stop-gain-dependent asset allocation strategies is also the most obvious: their potential to mitigate portfolio variance and drawdown. While it is reasonable to expect the asset allocation strategy to match the return of a balanced index or "constant mix" strategy with close average allocations to the strategy itself, the real benefit of the strategy is to further decrease portfolio variance relative to an investment in a balanced index or straight equities, especially during highly volatile periods. In fact, the maximum drawdown or 'peak-to-valley' for the strategy from 1990 to

Table 2: Asset allocation stop-loss, stop-gain strategy: $I = 4$, $J = 4$, $Z = .5$

Annual geometric return	8.45%
Annual arithmetic return	9.01%
Annualized standard deviation	9.41%
Information ratio	0.9
VFINX, Vanguard 500 index fund	
Annual geometric return	7.50%
Annual arithmetic return	9.06%
Annualized standard deviation	18.76%
Information ratio	0.4
Balanced 70–30 Portfolio (70% VFINX, 30% VWESX)	
Annual geometric return	7.16%
Annual arithmetic return	7.71%
Annualized standard deviation	12.98%
Information ratio	0.55
VWESX, Vanguard investment-grade bond fund	
Annual geometric return	4.57%
Annul arithmetic return	4.87%
Annualized standard deviation	8.92%
Information ratio	0.51

Note: Information Ratios are simply defined as annual geometric return over annualized standard deviation of return (risk-free rates are not subtracted for Information Ratio calculations, separating the calculation from the Sharpe Ratio).

2012 was 30.58%, compared to 55.47% for VFINX, the S&P 500 index fund. This represents one of the largest benefits of the strategy for institutional and retail investors who are, oftentimes, more concerned about not losing money than they are about outperforming the stock market each and every year.

In line with this, is the finding that the asset allocation stop-loss, stop-gain strategy has experienced far better returns than the "constant mix" or "buy-and-hold" strategies in significant market crises or "bear" markets. Of course, my strategy mechanically mitigates losses in large market declines, so long as the correlation of the portfolio investment assets diverges during these declines. And, while it is common to hear market participants speak of how assets converged toward correlations of 1 in 2008, there is only very limited and misleading truth to this statement (individual stocks did; however, broad asset groups *did not*). Notice, VWESX only had a −2.46% return in 2008, when VFINX had a brutal −36.66% return. Similarly, in 2002 when VFINX fell over 22%, VWESX actually gained over 10%. And, in fact, when one separates the 23-year dataset into a 2002 and 2008 dataset which is representative of market crises, and a dataset including the other 21 years, one finds that the daily correlation between VFINX and VWESX was −.1 in the 21-year period excluding market crises, but roughly −.37 in the two years in which equity markets experienced a loss of over −20%, 2002 and 2008 (and this difference is highly statistically significant)! With a clear time-varying correlation structure in place, at a time of crisis stop-losses on the asset declining swiftly in value (equities) will be triggered as the strategy naturally takes advantage of the typical 'flight to safety' of investor funds into the other asset (bonds). Thus, the strategy benefits from the 'decoupling' effect or nonconstant correlation structure between equities and bonds noted by Gulko (2002).

In Table 3, the annual returns for the strategy, VFINX, VWESX, and a 70–30 balanced index are listed. In Table 4, a CAPM alpha and beta for the strategy is estimated over the 23-year period. Results of a Fama-French Carhart regression are included in Table 5 below using the size (SMB) and book-to-market (HML) factors of Fama and French (1993) and the momentum (UMD) factor of Carhart (1997). Notice, the strategy had some of its worst raw returns in 2008 and 2002. However, as one may expect, the strategy outperformed VFINX by a wide margin in both years, over 19% in 2008 and by over 15% in 2002.

Also notice that the strategy has a statistically significant CAPM alpha of approximately 2 bp (.02%) daily or 513 bp (5.13%) annually. Again, this seems to be an impressive mark for a strategy that simply moves assets between stock and bond index funds based on predefined, fixed stop-loss and stop-gain rules. In addition, the strategy has a similar, positive and significant Fama-French Carhart alpha of roughly 2 bp a day. Thus, we can conclude that the strategy is

Table 3: Annual Returns, Asset Allocation stop-loss, stop-gain strategy ($I = 4$, $J = 4$, $Z = .5$) compared to VFINX, VWESX, and a 70–30 balanced index of the two

Year	*Strategy (%)*	*VFINX Return (%)*	*VWESX Return (%)*	*70–30 Index (%)*
2012	13.81	15.21	7.33	12.85
2011	11.92	1.17	12.68	4.62
2010	18.46	12.81	7.19	11.12
2009	20.50	25.47	5.14	19.37
2008	−17.00	−36.66	−2.46	−26.40
2007	1.34	4.91	0.67	3.64
2006	7.62	14.67	−0.20	10.21
2005	8.09	4.34	2.30	3.73
2004	6.64	10.13	5.88	8.85
2003	25.42	28.23	3.32	20.76
2002	−6.65	−22.44	10.09	−12.68
2001	−6.40	−11.28	5.74	−6.17
2000	−0.14	−9.17	8.85	−3.76
1999	5.89	19.97	−9.11	11.24
1998	36.98	28.11	4.37	20.99
1997	9.66	32.70	10.93	26.17
1996	14.74	21.11	−2.90	13.90
1995	30.17	37.23	24.30	33.35
1994	−4.36	0.58	−7.55	−1.86
1993	13.08	9.57	8.77	9.33
1992	6.70	3.67	0.38	2.68
1991	19.51	27.26	10.10	22.11
1990	−8.72	−9.27	−0.72	−6.70

Note: The 1990 return is partial year (July 2–Dec 31).

Table 4: A CAPM regression of the daily returns of the Asset Allocation stop-loss, stop-gain strategy from 1990–2012 is provided below

Coefficient	*Estimate*	*t stat*	*p value*
Alpha	.0002153***	2.73	.0063
Beta	−.0081599	−1.214	.2248
R^2			.0002

* = significant at a *p* value of .10.
** = significant at a *p* value of .05.
*** = significant at a *p* value of .01.
Note: Ken French's data available on his website is used in estimating $R_m - R_f$.

Table 5: A Fama–French Carhart regression of the daily returns of the Asset Allocation stop-loss, stop-gain strategy from 1990–2012 is provided below

Coefficient	*Estimate*	*t stat*	*p value*
Alpha	.0002035***	2.586	.0097
Beta	−.005519	−.773	.4395
SMB	.0007027***	5.32	<.0001
HML	.0004194***	3.07	.0021
UMD	−.0000125	−.13	.90
Adj. R^2			.0057

* = significant at a *p* value of .10.
** = significant at a *p* value of .05.
*** = significant at a *p* value of .01.
Note: Ken French's data, available on his website, is used in estimating $R_m - R_f$, SMB, HML, and UMD.

not simply profiting off of exposure to the known Fama–French Carhart factors or market risk. However, since the strategy simply allocates one's portfolio between equities and bonds, and not individual stocks, it would make little sense if SMB, HML, or even UMD explained away the strategy's returns altogether as these factors explain the cross section of stock returns, rather than aggregate stock or bond market returns. A 'market timing' factor would do more to explain the returns of my strategy; however, there is ironically no prediction of market returns within my model (that is the point)! The point is that intelligent (or even fairly unintelligent, simplistic, and mechanical…) risk-controls utilizing stop-losses and stop-gains seem to 'time' the market rather well. And, this again can only be due to a nonconstant correlation structure between the assets held in one's portfolio. While Kaminski and Lo (2007) do not focus on this intuition, it is in line with their finding of a stop-loss strategy (seemingly oddly) avoiding market downturns. As I will show, the appropriate explanation for at least a portion of the strategy's alpha is the nonconstant correlation structure between equities and bonds, and in particular the divergent correlations typically witnessed in market crises.

While it is not surprising that the asset allocation strategy reduces variance alone relative to an investment in equities or perhaps even a 70–30 balanced fund, the positive effects of stop-loss and stop-gain rules go beyond a reduction in portfolio volatility. For instance, even if the strategy only matched the return of equities or even a balanced fund, one could easily argue that it is an improvement on either since it has lower tail-risk as measured by maximum drawdown and other basic statistical measures (it also has less negative skewness). The tail-risk benefit of the strategy is well portrayed in a simple graphical setting. Therefore, I display the monthly return distribution of the strategy and VFINX and over the sample period with histograms in Figures 1 and 2 and encourage one to pay particular attention to both the negative return outliers and scale in each figure.

Finally, it is very important to note that the much lower variance inherent in the strategy leads to higher long-term returns and higher annual geometric returns than equities even if the average daily or monthly returns of the strategy are only approximately the same, or even slightly lower than equities. Mathematically, this is just an application of Jensen's Inequality and the resulting gap between geometric and arithmetic returns (Jensen, 1906).

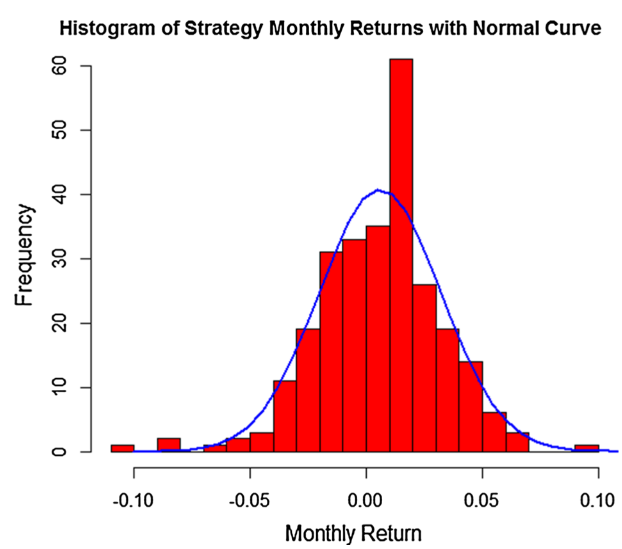

Figure 1: Histogram of Asset Allocation stop-loss, stop-gain strategy monthly returns with normal curve.

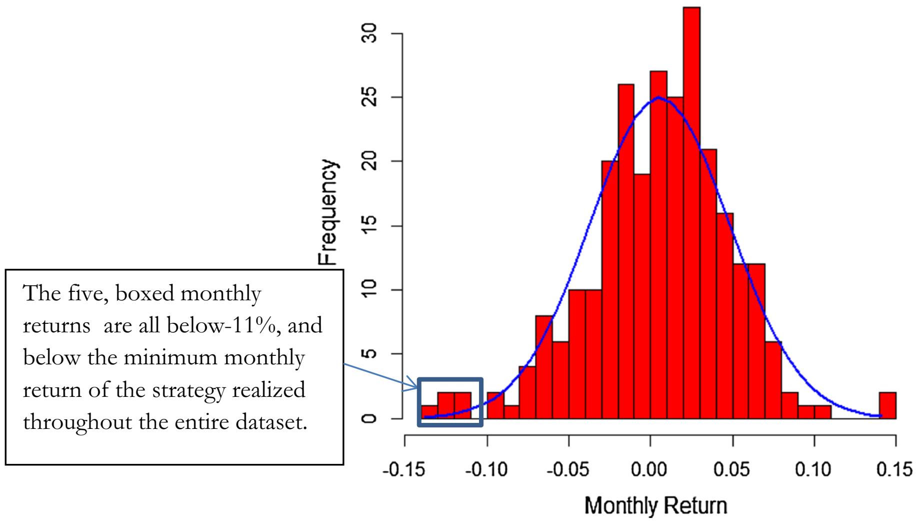

Figure 2: Histogram of VFINX monthly returns with normal curve.

Reasonable, long-term investors interested in the optimal asset allocation of their portfolio will be concerned with long-term geometric rather than short-term arithmetic returns as long-term geometric returns are an actual measure of the compounding of one's money or portfolio value over time. Daily returns should be all but unimportant to a prudent, rational long-term investor utilizing zero leverage within a conservative strategy. Since, mechanically, my strategy 'smoothes' returns, the gap between the strategy's average geometric return and its average arithmetic return over any time period is much smaller than the gap between the average geometric return and average arithmetic return of a more volatile strategy. More so, this gap between actual or geometric return and a simple average of return grows the longer the time period considered (more time for returns to compound). Of course, the higher the variance of an asset, the higher the difference between its geometric and arithmetic returns across any time period and the longer an investor's investment horizon the larger the economic impact to the investor. Thus, the 'smoothing' of returns inherent in this long-term strategy not only mitigates risk, but it also boosts long-term real returns quite dramatically to an investor relative to investment in equities ("buy-and-hold") or even balanced funds ("constant mix"). In addition, this benefit is realized most when one demands it most, in volatile markets. Thus, 'smoothing' of returns within the strategy is another benefit to investors rightfully concerned with the long-term return, volatility, and maximum drawdown of their portfolios.

ROBUSTNESS CHECK

While the risk-adjusted returns of my strategy are enticing, there is certainly an absolute need to show the robustness of the results I present. In particular, I perform tests to alleviate any concern that the encouraging results from my strategy are not just a byproduct of lucky (or even purposeful) selection of the exogenous inputs. The baseline strategy considered has 4 stop-loss levels ($I = 4$), 4 stop-gain levels ($J = 4$), and fixed-spreads between stop-loss and stop-gain levels of ½ of the 6-month lagged annualized standard deviation of return of the asset held in each position ($Z = .5$). Thus, the strategy is composed of 16 positions with stop-loss and stop-gain levels of $\delta_1 = (.5, .5)$, $\delta_2 = (.5, 1), \ldots, \delta_{16} = (2, 2)$. Since a two standard-deviation return outlier (in terms of annualized volatility of the 6-month lagged return) is obviously relatively rare and a ½ standard deviation return occurs relatively frequently, the baseline asset allocation stop-loss, stop-gain strategy was purposely specified to neither have such tight stops placed on positions that reallocations are constantly triggered nor to have such wide stops on positions that reallocations are never triggered.

Thus, my robustness check is simply a number of reasonable respecifications of I, J, and Z, with the investment assets unchanged so that asset 1 is still VFINX and asset 2 VWESX. The goal is to verify that similar strong return and mitigated risk characteristics are exhibited by the strategy across different reasonable combinations of the exogenous inputs. Since an investor in my stop-loss, stop-gain strategy must specify the number of stop-loss and stop-gain levels as well as the spread between levels *prior* to investment, it is extremely prudent to show that the strategy's strong long-term results are not overly sensitive to reasonable respecifications of I, J, and Z.

Therefore, for the robustness check, I and J are respecified at $(I, J) = \{(2, 2), (3, 3), (4, 4), (5, 5)\}$. Notice that only specifications in which I and J are equal are considered. Specifications of I and J in which $I < J$ so that losses are cut quickly and gains are left on the table are not. Similarly, specifications in which $J < I$ are also not considered. While the question of optimal stop-loss and stop-gain placement on asset groups and whether losses should be cut quickly and 'winners left to run' is certainly an interesting one which demands more work and may be testable from my model, it is also second-order question beyond the scope and purpose of this paper. Also, notice that $(I, J) = (1, 1)$ is not considered. In an $I = 1$ and $J = 1$ specification, there is only one position held at any point in time, here solely equities or bonds, and therefore no diversification benefit could be derived. For that reason, an $I = 1$ and $J = 1$ specification is considered to clearly be suboptimal, as it does not clearly add to the expected return of the strategy yet clearly adds to expected volatility relative to all other specifications.

Within the robustness checks Z is specified at four different levels: $Z = .25$, .5, .75, and 1. Thus, 16 total specifications are performed (15 of which are true robustness checks, and one of which is the baseline, $I = 4$, $J = 4$, and $Z = .5$). The results of all are shown in Table 6.

Notice, the results of the robustness check strongly confirm the strength of the asset allocation stop-loss, stop-gain strategy and reject the reasonable concern that I, J, and Z were simply 'hand-picked' or calibrated in order to produce favorable or even optimal results.

All 16 specifications have significantly less variance than both the balanced fund and the S&P index fund. Thus, it seems the stop-loss, stop-gain strategy decreases risk relative to both "buy-and-hold" and "constant mix" investing. In addition, 14 out of the 16 (87.5%) of specifications tested beat the raw return of the balanced index and 12 out of 16 (75%) beat the raw return of VFINX (S&P index fund) over the period from July 2, 1990 to Dec 31, 2012. According to US News, from 2008 to 2012 only 27% of equity mutual funds beat their relevant S&P index benchmark (Silverblatt, 2012). And, this is without even considering the added risk many funds may have taken on in an attempt to do so. In the robustness check, all portfolios have an annualized return standard deviation between 8% and 12%. All have Information Ratios which are greater than that of VFINX, VWESX, or a balanced index, indicating that the strategy has historically *completely dominated* "buy-and-hold" and "constant mix" strategies in terms of risk-adjusted return.

In short, the asset allocation stop-loss, stop-gain strategy I create is quite robust to

Table 6: Overall statistics for the 15 respecifications of the Asset Allocation stop-loss, stop-gain strategy as well as the baseline ($I = 4$, $J = 4$, $Z = .5$)

I	*J*	*Z*	*Annualized geometric return (%)*	*Annualized σ (%)*	*P (F <=f)*	*Return >70–30?*	*Return > S&P?*	*Information ratio*
2	2	0.25	6.19	10.28	<.0001	No	No	0.6
3	3	0.25	7.04	10.85	<.0001	No	No	0.65
4	4	0.25	7.44	10.98	<.0001	Yes	No	0.68
5	5	0.25	8.77	11.20	<.0001	Yes	Yes	0.78
2	2	0.5	7.35	10.41	<.0001	Yes	No	0.71
3	3	0.5	7.97	10.52	<.0001	Yes	Yes	0.76
4	4	0.5	8.45	9.41	<.0001	Yes	Yes	0.9
5	5	0.5	9.56	9.85	<.0001	Yes	Yes	0.97
2	2	0.75	8.06	9.65	<.0001	Yes	Yes	0.84
3	3	0.75	8.68	8.96	<.0001	Yes	Yes	0.97
4	4	0.75	8.48	9.44	<.0001	Yes	Yes	0.9
5	5	0.75	8.64	10.67	<.0001	Yes	Yes	0.81
2	2	1	9.37	8.81	<.0001	Yes	Yes	1.06
3	3	1	8.63	9.13	<.0001	Yes	Yes	0.94
4	4	1	8.16	9.82	<.0001	Yes	Yes	0.83
5	5	1	8.09	11.62	<.0001	Yes	Yes	0.7
Average			8.18	10.10		87.5% "Yes"	75% "Yes"	0.82

Note: The $P(F <= f)$ gives the probability that the variance of the daily returns of the respecification is greater than that of the 70–30 balanced index. The "Return >70–30" and "Return > S&P" columns display "Yes" if the specification's raw geometric return beats that of the 70–30 balanced index or VFINX, respectively. All results are for the period of 1990–2012.

reasonable changes in the exogenous parameters picked, indicating that it, or a variant of it, likely has valuable use as an asset allocation tool in practice. The strategy maintains its very low volatility and superior risk-adjusted return characteristics given reasonable respecifications of the necessary exogenous parameters.

It is surprising to many that such a simplistic strategy, focused only on risk-control rules, can outperform other asset allocation frameworks. In order to help justify my argument that a significant portion of the strategy's alpha is due to the nonconstant correlation structure between stocks and bonds, I create a Monte Carlo model and run the strategy on thousands of years of simulated equity and bond returns across different market scenarios.

MONTE CARLO SIMULATION

I create and run MC simulations to model the daily returns of stocks and bonds over 20-year periods and test the stop-loss, stop-gain dynamic asset allocation strategy's performance within differing market states relative to 'buy-and-hold' investment strategies.

Within the MC simulations, my primary assumption is that there are two possible states for the stock market: a 'normal' market or a 'crisis' market. Within 'normal' markets, the daily returns of bonds have a constant correlation of p_n to the daily returns of equities. Within 'crisis' markets, in which an economic shock occurs, the daily return correlation of bonds to equities is p_c. Thus, my Monte Carlo simulations are able to model the nonconstant correlation structure between stocks and bonds and the 'decoupling' effect between major asset groups noted by Gulko (2002).

As noted above, at any point in time within each MC simulation the state of the stock market is either 'normal' or 'crisis.' Furthermore, the market may only transition states on an annual basis (every 252 trading days). The probability of a stock market 'crisis' in any given year is designated λ. Therefore, the probability of a 'normal' stock market in any given year is $1 - \lambda$. More formally,

(1) The state of the stock market, S, in any year is a binomial random variable with probability of a 'crisis' λ: $S \sim B(1, \lambda)$. If $S = 1$, the market is a 'crisis' market during the given year, and if $S = 0$, the market is a 'normal' market during the given year.

In 'normal' years, the mean daily return of the stock market is assumed to be the historical mean daily return of the S&P 500 from 1990 to 2012, excluding 2002 and 2008 as these were significant stock market downturns of over −20% annually for the S&P 500 Index and are considered 'crisis' years. The stock market's return variance in 'normal' years follows a GARCH (1, 1) process with the parameters α_0, α_1, and b_1 calibrated to historical 1990–2012 S&P 500 Index daily return data with 2002 and 2008 discarded. Following GARCH (Generalized Autoregressive Conditional Heteroscedasticity), stock market volatility at time t follows a stochastic process defined by Bollerslev and Mikkelsen (1996) and well-described by Hansen and Lunde (2005). Specifically, the GARCH(p, q) model states that variance at time t, here denoted v_t, is a function of the level of variance over the last p periods, and volatility shocks or model error-terms over the past q periods. More formally, the GARCH(p, q) model states the following:

(a) $\in_t$ is the error-term of the stochastic variance process at time t. $\in_t$ is normally distributed with variance, v_t. Therefore,

$$\in_t = u_t\sqrt{v_t}$$

where u_t is a random draw from a standard normal distribution so that $u_t \sim N(0, 1)$.

(b) Variance at time t is a function of the last q period's squared error-terms, and the last p period's realized variances. Therefore, the GARCH(p, q) model can be written as

$$v_t = \alpha_0 + \sum_{i=1}^{q} \alpha_i \in_{t-1}^2 + \sum_{i=1}^{p} b_i v_{t-1}.$$

(c) By setting $p = 1$ and $q = 1$, only last period's squared error-term and variance remain so that the GARCH(1, 1) model is condensed to the following autoregressive stochastic process:

$$v_t = \alpha_0 + \alpha_1 \in_{t-1}^2 + b_1 v_{t-1}.$$

Using maximum likelihood estimation (MLE),$\hat{\alpha}_0$, $\hat{\alpha}_1$, and $\hat{b}_1$ are estimated using 1990–2012 S&P 500 Index daily return data excluding 2002 and 2008. Then, in each 'normal' year a random stock market stochastic volatility path over 252 trading days (one year) is simulated in which stock market volatility follows a GARCH(1, 1) process with parameters equal to $\hat{\alpha}_0$, $\hat{\alpha}_1$, and $\hat{b}_1$.

In 'crisis' years, annualized stock market returns are assumed to follow a normal distribution. Average 'crisis' stock market return and stock market volatility are both exogenously set. I explain the reasoning for the 'crisis' stock market average annualized return and annualized return volatility parameters I pick within the scenarios I define below. Formally, within the MC simulations the stock market return dynamics are as follows:

(2) If $S = 1$, then the stock market is in a 'crisis' market. Within a 'crisis' market, daily stock market returns are normally distributed and IID. Average annual return and annualized volatility of the stock market in a 'crisis' market are both exogenously set. Stock market returns are normally distributed in the 'crisis' market with an annualized mean return $\mu_{\tilde{M}}$ and annualized variance $\sigma_{\tilde{M}}^2$. Therefore, the annualized crisis return of the stock

market (M) in year i is denoted as follows (the tilde denotes a 'crisis' market):

$$r_{i,\tilde{M}} \sim N\left(\mu_{\tilde{M}}, \sigma^2_{\tilde{M}}\right).$$

(3) If $S = 0$, then the state of the stock market is 'normal.' Daily stock market return volatility is determined by a random stochastic volatility path following a GARCH(1, 1) model over 252 trading days (one trading year) with parameters equal to $\hat{\alpha}_0$, $\hat{\alpha}_1$, and $\hat{b}_1$. The mean daily return of the stock market is calibrated to the mean daily return of the S&P 500 Index over 1990–2012 excluding 2002 and 2008. Therefore, the daily return of the stock market on any day $t : t \in \{1, \ldots, 252\}$ within a 'normal' year i is

$$r_{i,t,M} \sim N(\mu_M, v_t),$$

where μ_M is the average daily return of the S&P 500 over 1990–2012 excluding 'crisis' periods of 2002 and 2008 and v_t is the stochastic variance of the stock market on day t. $v_{1\ldots}v_{252}$ are determined from a random stochastic volatility path following a GARCH(1, 1) model with parameters $\hat{\alpha}_0$, $\hat{\alpha}_1$, and $\hat{b}_1$ calibrated to daily S&P 500 Index data from 1990 to 2012 excluding 2002 and 2008.

As stated initially, within 'normal' markets daily bond returns have a correlation of ρ_n to daily stock market returns. Within 'crisis' markets, this correlation diverges to ρ_c. The 'normal' correlation in all simulations, ρ_n, is estimated based on the correlation of the S&P 500 Index and VWESX from 1990 to 2012 excluding 2002 and 2008. The correlation between the S&P 500 and VWESX over the 'normal' portion of this sample period is roughly $-.1$. The 'crisis' correlation between stocks and bonds, ρ_c, varies between scenarios in order to compare the effect of time-varying correlations on the strategy's performance.

In scenario (a), the correlation in 'crisis' markets, ρ_c, is set to $-.4$, as $-.37$ was the realized correlation between the S&P 500 and VWESX in 2002 and 2008. In the other scenarios, (b) and (c), the correlation in 'crisis' markets is set to -.1, representing no 'divergence' at all or a static correlation structure between the stock and bond markets. Therefore, more formally,

(4) If $S = 0$, the correlation between stocks and bonds over the year is the 'normal' correlation, ρ_n, set to $-.1$, the approximate realized correlation of the S&P 500 to VWESX over 1990–2012 excluding 2002 and 2008. If $S = 1$, the correlation between stocks and bonds is the 'crisis' correlation, ρ_c, which is exogenously set by the user, and takes on values of $-.4$ or $-.1$ within scenarios (a), (b), and (c) tested.

For simplicity, bond returns are assumed to be normally distributed in both 'normal' and 'crisis' markets. In 'normal' markets, average annualized bond returns and annualized bond volatility are calibrated to the realized values for VWESX over the 'normal' sample period of 1990–2012 excluding 2002 and 2008. Formally,

(5) If $S = 0$, bonds are assumed to follow a normal distribution such that the return of bonds (B) in year i is

$$r_{i,B} = N\left(\mu_B, \sigma^2_B\right),$$

where μ_B is the average annualized return of VWESX over 1990–2012 excluding 2002 and 2008 and σ^2_B is the annualized variance of VWESX over the same period.

(6) If $S = 1$, bonds are assumed to follow a normal distribution such that the return of bonds (B) in year i is

$$r_{i,\tilde{B}} = N\left(\mu_{\tilde{B}}, \sigma^2_{\tilde{B}}\right),$$

where $\mu_{\tilde{B}}$ and $\sigma^2_{\tilde{B}}$ are exogenously set and $\mu_{\tilde{B}}$ varies between scenarios as the profitability of the stop-loss, stop-gain asset allocation strategy is heavily dependent on mean 'crisis' bond returns, $\mu_{\tilde{B}}$ (as well as ρ_c).

The Monte Carlo simulation defined above is run for 1000 simulations of 20 years of daily data per scenario. Three different scenarios are tested: a 'Decoupling' scenario which most closely mirrors the realized data over 1990–2012 in which significant divergence in US stock and bond market correlations and realized returns occurred during financial crises (scenario (a)), a 'Mild decoupling' scenario (scenario (b)), and a 'No Decoupling' scenario (scenario (c)). The scenario parameters are discussed in further detail below.

By using realistic, yet conservative inputs for the simulations in scenarios (a), (b), and (c), we are better able to determine if the strategy is likely to continue to attain returns in line with its strong historical performance over the 1990–2012 sample period. In particular, these Monte Carlo simulations can help validate that the period did not just happen to be a particularly fortunate time-series for the strategy. In addition, by changing the inputs, particularly the probability of a 'crisis' market occurring, λ, or the correlation between stocks and bonds during crises, ρ_c, we may better understand how the effect of broad asset 'decoupling' in times of financial crisis affects the profitability of stop-loss and stop-gain rule-based dynamic asset allocation strategies. In Table 7 definitions of the MC simulation estimators are given and in Tables 8, 9, and 10 below the results of the Monte Carlo simulation for scenarios (a), (b), and (c) are displayed.

In the first scenario with results reported in Table 8, I estimate λ to be .05, which is a conservative estimate of the probability of a 'crisis' market in line with 1990–2012 historical data. 2002 and 2008 are easily identified as 'crisis' years within this period as in each year the S&P 500 declined by over −20%. In addition, there is a reasonable argument to be made that 1999 should similarly be defined as a 'crisis' year. However, even with only 2002 and 2008 identified as crises, 8.7% of years (2/23) are 'crises' in the sample period of 1990–2012. Of course, with so few crisis years and a relatively small dataset, it is entirely impossible to accurately estimate λ with any reasonable precision. Still, 5% or 1 in 20 years seems to be a reasonable, if not even conservative, starting point for the probability of a 'crisis' market. In addition, in scenario (a), I set the crisis correlation, ρ_c, to −.4 which is closely in line with the correlation of equities to bonds in the 'crisis' years of 2002 and 2008 (−.37). I set the normal correlation, ρ_n, to −.1 since this is approximately the daily correlation of equities to bonds in the 1990–2012 period excluding 2002 and 2008. The mean annualized stock market 'crisis' return, $\mu_{\tilde{M}}$, is set to −20% with a 15% standard deviation, $\sigma_{\tilde{M}}$. The mean annualized bond market 'crisis' return, $\mu_{\tilde{B}}$, is set to 0% with a 10% annualized standard deviation, $\sigma_{\tilde{B}}$. Both parameters are sensible based on the 1990–2012 sample period but in the same

Table 7: MC simulations

Within the simulations below the estimators denote the following
$\hat{\mu}_M$ = Estimated annualized geometric return of the Stock Market
$\hat{\mu}_B$ = Estimated annualized geometric return of the Bond Market
$\hat{\mu}_{SL}$ = Estimated annualized geometric return of the baseline Asset Allocation stop-loss, stop-gain strategy
$\hat{\sigma}_M$ = Estimated annualized volatility of the Stock Market
$\hat{\sigma}_B$ = Estimated annualized volatility of the Bond Market
$\hat{\sigma}_{SL}$ = Estimated annualized volatility of the baseline Asset Allocation stop-loss, stop-gain strategy
$\widehat{IR}_M$ = Information Ratio of the Stock Market
$\widehat{IR}_B$ = Information Ratio of the Bond Market
$\widehat{IR}_{SL}$ = Information Ratio of the baseline Asset Allocation stop-loss, stop-gain strategy

Table 8: MC simulation results of the 'Decoupling' Scenario (scenario (a)). The table contains the results from 1000 simulations of 20 years of equity and bond data, and the performance of the Asset Allocation stop-loss, stop-gain strategy on this simulated data

Estimator	$\hat{\mu}_M$ (%)	$\hat{\sigma}_M$ (%)	$\widehat{IR}_M$	$\hat{\mu}_B$ (%)	$\hat{\sigma}_B$ (%)	$\widehat{IR}_B$	$\hat{\mu}_{SL}$ (%)	$\hat{\sigma}_{SL}$ (%)	$\widehat{IR}_{SL}$
MC estimate	5.94	18.29	0.33	4.37	8.98	0.49	6.45	11.19	0.58
SE	0.14	0.05	0.01	0.07	<0.01	0.02	0.09%	0.04%	0.01

Note: Results are reported for equities, bonds, and the baseline Asset Allocation stop-loss, stop-gain algorithm. The normal correlation is set to −.1 and crisis correlation is set to −.4. The mean returns and volatilities of stocks and bonds in normal times are calibrated from the 1990–2012 data. The annual crisis probability is 5%. The mean crisis annualized equity return is −20% with a 15% standard deviation. The mean crisis bond return is 0% with a 10% standard deviation.

Table 9: MC simulation results of the 'Mild Decoupling' Scenario (scenario (b)). The table contains the results from 1000 simulations of 20 years of equity and bond data, and the performance of the Asset Allocation stop-loss, stop-gain strategy on this simulated data

Estimator	$\hat{\mu}_M$ (%)	$\hat{\sigma}_M$ (%)	$\widehat{IR}_M$	$\hat{\mu}_B$ (%)	$\hat{\sigma}_B$ (%)	$\widehat{IR}_B$	$\hat{\mu}_{SL}$ (%)	$\hat{\sigma}_{SL}$ (%)	$\widehat{IR}_{SL}$
MC estimate	6.09	18.32	0.34	3.79	8.98	0.42	6.11	11.22	0.55
SE	0.14	0.05	0.01	0.07	<0.01	0.01	0.09	0.04	0.03

Note: Results are reported for equities, bonds, and the baseline Asset Allocation stop-loss, stop-gain algorithm. Both the normal and crisis equity correlation is set to −.1. The mean returns and volatilities of stocks and bonds in normal times are calibrated from the 1990–2012 data. The annual crisis probability is 5%. The mean crisis annualized equity return is −20% with a 15% standard deviation. The mean crisis bond return is −10% with a 10% standard deviation.

Table 10: MC simulation results of the 'No Decoupling' Scenario (scenario (c)). The table contains the results from 1000 simulations of 20 years of equity and bond data, and the performance of the Asset Allocation stop-loss, stop-gain strategy on this simulated data

Estimator	$\hat{\mu}_M$ (%)	$\hat{\sigma}_M$ (%)	$\widehat{IR}_M$	$\hat{\mu}_B$ (%)	$\hat{\sigma}_B$ (%)	$\widehat{IR}_B$	$\hat{\mu}_{SL}$ (%)	$\hat{\sigma}_{SL}$ (%)	$\widehat{IR}_{SL}$
MC Estimate	7.55	18.23	0.42	4.62	8.92	0.52	7.38	11.18	0.67
SE	0.14	0.05	0.01	0.07	<0.01	0.02	0.09	0.04	0.01

Note: Results are reported for equities, bonds, and the baseline Asset Allocation stop-loss, stop-gain algorithm. The normal correlation is set to −.1 and the mean returns and volatilities of stocks and bonds in normal times are calibrated from the 1990–2012 data. The annual crisis probability is 0%. As such, no other crisis parameters need to be defined.

manner as λ are naturally imprecise as we have few 'crisis' data points to consider. Thus, in scenario (a), the significantly higher expected return of bonds versus equities during crises along with the divergent correlation structure of bonds to equities during financial crises is roughly in line with what was actually observed over the 1990–2012 period. The scenario fully, yet conservatively models 'decoupling' in line with historical data. Therefore, scenario (a) is referred to as the 'Decoupling' scenario.

In the second scenario with results reported in Table 9, a 'Mild Decoupling' effect is simulated. Instead of an expected annualized bond return of 0% during crises, I conservatively estimate the mean annualized bond return during crises, $\mu_{\tilde{B}}$, to be a less favorable −10% ('less favorable' to the stop-loss, stop-gain asset allocation strategy return relative to that of a "buy-and-hold" strategy). In addition, within scenario (b) the correlation of equities to bonds during crises, ρ_c, stays fixed at −.1 instead of diverging to −.4, eliminating the diverging correlations component of the 'decoupling' effect. All other parameters in scenario (b) are identical to those set in scenario (a) above. Thus, within scenario (b) there is a much milder simulated 'flight to quality' from equities to bonds during crisis markets and less safe harbor within fixed income assets than within scenario (a). Therefore, scenario (b) very mildly and to a limited extent simulates the effect of 'decoupling' during financial crises and is referred to as the 'Mild Decoupling' scenario.

In the third scenario with results reported in Table 10, I eliminate the 'decoupling' effect altogether by setting the probability of a market 'crisis,' λ, to 0%. Thus, in scenario (c) the volatility path of equities always follows a GARCH(1, 1) process with parameters calibrated to the 1990–2012 data, excluding the 'crisis' years of 2002 and 2008. In addition, the correlation of bonds to equities stays fixed at the 'normal' correlation, ρ_n, of -1. Of course, there is no need for any specification of the mean stock or bond market 'crisis' return or variance parameters within scenario (c) as market crises simply do not exist within the scenario. All 'normal' parameters for the return and variance of stocks and bonds within scenario (c) are the same as those used in scenarios (a) and (b) above. This scenario of 'No Decoupling' is a very purposeful oversimplification. Market crises are completely avoided in order to test the performance of the stop-loss, stop-gain dynamic asset allocation strategy in 'normal' markets alone.

Reasonably, one should expect the estimated stop-loss, stop-gain strategy geometric return and information ratio relative to those of a "buy-and-hold" strategy to be best in the first scenario ('Decoupling'), then the second ('Mild Decoupling'), and then the third ('No Decoupling'). The results bear this out exactly.

We observe a 6.45% geometric return to the strategy versus 5.94% to equities in scenario (a), the 'Decoupling' scenario, which incorporates decoupling and nonconstant asset correlations. In scenario (b), the 'Mild Decoupling' scenario, which assumes mild decoupling but constant asset correlations, we see a 6.11% geometric return to the strategy vs. 6.09% to equities. Finally, in scenario (c), the 'No Decoupling' scenario in which market crises never occur, we see a 7.38% return to the strategy vs. 7.55% for equities. These results further reiterate the notion that the existence of nonconstant asset correlations and a flight to safety from equities to bonds during market crises benefits the return of the stop-loss, stop-gain dynamic asset allocation strategy relative to a 'buy-and-hold' investment strategy.

Of course, no scenario or MC simulation of any sort matches the return dynamics of the equity and bond markets perfectly and one may rationally argue that the *actual* equity and bond market dynamics are somewhere between scenario (a) and scenario (c). While I was purposely conservative in specifying the parameters within all scenarios, I fully understand and accept this rationale. That said, I point out that the information ratio of the stop-loss, stop-gain strategy dominates that of both equities and bonds in *all three scenarios* by a large and statistically significant margin. This finding that the risk-adjusted return of a stop-loss, stop-gain rule-based dynamic asset allocation strategy outperforms that of equities or bonds *even in completely normal markets devoid of jumps, large downturns, or time-varying correlations* is a surprising benefit of such a strategy. The likely explanation is that there is still enough equity market volatility through the use of the GARCH(1,1) model within normal markets for an investor to benefit by decreasing his allocation to equities when the lagged return to equities is quite volatile. In other words, implicit downside volatility protection is still a benefit of such a strategy due to the stochastic nature of volatility in which large volatility spikes tend to be preceded by smaller spikes. This finding only helps strengthen the robustness of the result that asset allocation strategies which utilize stop-losses and stop-gains need more investigation as an alternative and viable form of dynamic asset allocation.

CONCLUSION

In totality, we see that asset allocation strategies which utilize stop-loss and stop-gain rules in order to mitigate risk may have significant potential to enhance portfolio risk-adjusted return and limit portfolio drawdown. By allocating assets in one's portfolio through the use of stop-loss and stop-gain rule-based algorithms, one may be able to reduce portfolio variance, while not sacrificing long-term return.

Given that the results I observe from calculating historical returns, estimating factor model regressions, conducting robustness checks, and developing and running MC simulations for varying market scenarios are all broadly consistent; I believe that asset allocation strategies which incorporate stop-loss and stop-gain rules likely offer a valuable alternative approach to dynamic asset allocation. Mutual fund companies and ETF providers may be wise to consider the development of asset allocation funds which allocate investors' assets, at least in part, based on stop-loss and stop-gain or other risk minimization rules. More research is needed to investigate why dynamic asset allocation stop-loss, stop-gain strategies tend to outperform as these strategies show strong long-term risk-adjusted returns, even in historically nonvolatile markets.

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