ACHIEVE YOUR GOALS MORE OFTEN:
A CASE FOR ACTIVE ALLOCATION

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ABSTRACT

We propose a dynamic portfolio optimization procedure which uses markets to predict asset returns as well as risks. Differing from other approaches to outperformance, we couch this approach firmly in the concept of efficient markets. In effect *using* the efficiency of markets to outperform alternate buy-and-hold strategies. We also incorporate goals-based portfolio theory in an effort to create a strategy which can be used to help investors achieve their goals more often, as this is why most investors interact with public markets in the first place.

To build the optimization strategy, we use option market implied volatility to forecast the standard deviation of an asset in the coming month. To forecast returns in the coming month, we utilize the US Treasury yield curve spread (10-Year minus 3-month) as a probability indicator of coming recessions, then use the probability-weighted sum of returns as the expected portfolio return in the coming month. This information is then used in place of historical return and variance expectations in the optimization model, and the asset allocation is re-optimized (and thus updated) each month. We tested 108 months (9 years), spanning the years 2007 through 2015.

When compared against a historically mean-variance optimized, passively-allocated portfolio, the active allocation approach presented and tested here delivers significant alpha, generally lower beta, and considerably higher probabilities of goal achievement. We find that the monthly increase in return over the passive portfolio (+10.25 basis points,

+52.15 basis points, and +64.05 basis points) generated by this strategy is statistically significant at the 5% significance level, though in one test we could not reject the null hypothesis at that level of significance.

We further find that, when compared to a simple "buy-and-hold the S&P 500" strategy, the active allocation strategy delivers alpha of 9.70, average excess monthly returns of +62 basis points (statistically significant at the 5% level), lower beta ($\beta = 0.57$), and considerably better risk/return efficiency (165% higher Sharpe Ratio).

These results are robust even after accounting for the effects of diversification, which leads us to conclude that the superiority of the approach can be attributed to the information content of market-based forecasts.

When interacting with public markets, most people are doing so to achieve some end-goal. It is difficult to imagine an investor saving and sacrificing, then wading into the tumultuous waters of public markets, all “for the fun of it”! In this context, the debates of traditional portfolio theory seem entirely irrelevant. After all, goals-based investors do not necessarily care what percentage a coin must land heads in order to *feel* comfortable with the risk taken—a long-standing debate in modern portfolio theory (see especially Markowitz [2010]). Goals-based investors care about achieving their goals!

Given that the efficient market hypothesis (EMH) is the academic and industry default today, this investigation will work under that assumption, offering theoretical and empirical evidence to show that, even assuming efficient markets, it is still possible to outperform on a risk-adjusted basis (create alpha). This investigation also shows how that outperformance can (and should) be channeled for the benefit of investors with goals to achieve.

In short, with the techniques presented here, investors have a higher probability of achieving their goals than they do with passive investing alone.

A QUICK TOUR: GOALS-BASED PORTFOLIO THEORY

Putting goals at the center of investment theory has only recently been a focus of academic portfolio theory, though practitioners have been using the approach for years. Having begun with the tax-sensitivity studies (institutions such as pension funds and endowments are not subject to taxes—one of their many advantages over individuals) of

Jeffrey and Arnott [1993], Brunel [1997] and [1998], goals-based portfolio theory has grown to include the important work of behavioral finance, most importantly the mental-accounting framework of Thaler [1985]; the Prospect Theory of Kahneman and Tversky [1979]; and the Behavioral Portfolio Theory of Shefrin and Statman [2000].

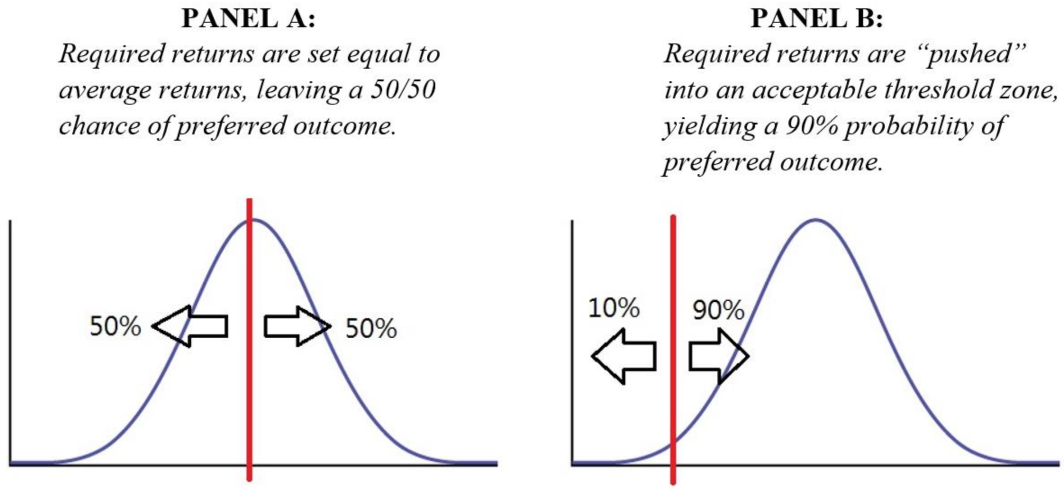
Recently, goals-based theory has caught the attention of investment icons, and a milestone was surely reached with the publication of Das, Markowitz, Scheid and Statman's [2010] paper "Portfolio Optimization with Mental Accounts" which effectively blended the behavioral work done by Shefrin and Statman with the mean-variance efficiency work done by Markowitz. Their work offers two very important insights.

First, rather than attempting to discern an investor's psychological risk tolerance (which is nigh impossible to pin down—see Pan and Statman [2012]), they proposed asking the investor a simple question: *what is the maximum probability of failing to achieve this goal that you are willing to accept?* The practitioner converts this expressed threshold into a risk-aversion coefficient, then proceeds to optimize the portfolio as usual. This at least acknowledges how goal-based investors perceive risk, and allows them to communicate to the practitioner in that language.

Brunel [2015, p. 83] takes this a step further and offers a basis in common language, asking the investor to speak of goal priority in terms of "needs, wants, wishes, and dreams." With regard to willingness to accept higher risks of achievement failure, he asks the investor to speak in terms of "nightmares, fears, worries, and concerns." This can help the practitioner classify which goals are priority (after all, everyone dies with some “dreams” unfulfilled), and which goals are worth reaching for but acceptable if left unfunded.

A second very critical observation of Das, et al [2010] is that investors must operate with a goals-based discount rate. This is best explained with the help of a picture (see Exhibit 1). By setting the average expected portfolio return equal to the required return, the practitioner has necessarily given only a 50% probability of goal-achievement (Panel A of Exhibit 1—the common approach in the industry). This is because, by definition, half the returns fall below the average (which means a failure to achieve a goal). Using a goal-based discount rate moves the distribution of outcomes to the right, pushing the required return into a zone where the majority of outcomes lie (Panel B of Exhibit 1—the goals-based approach). Notice that this means the portfolio must have a higher expected return that what is required (the red line in Exhibit 1 is the required return, the peak of the distribution is the expected return). This approach has been shown to give investors a higher probability of achieving their goals.

Exhibit 1: Two Approaches to Dealing with Required Returns



Another major departure from traditional portfolio theory is a redefinition of risk and reward (discussed extensively by Parker [2016a] and Parker [2016b]). While modern portfolio theory (MPT) equates risk with standard deviation and reward with expected returns, goals-based portfolio theory equates risk with the probability of achieving a goal and reward with excess wealth generated which is over-and-above the goal. This requires a separate mathematical understanding to properly model—a discussion revisited in later sections.

THEORETICAL SUPPORT: USING MARKETS TO PREDICT MARKETS

Market dynamics are understood today primarily through the lens of the efficient market hypothesis (EMH). Central to this idea is that market participants, driven by competition for riskless profit, will actively seek out and react to information as it becomes publically available. Of course, they will also remember what has already happened—so past data is also taken into account. As affirmation for such an idea, Fama [1970], Fama and French [2010], as well as others, have empirically shown the difficulty of outperforming markets with active management strategies.

We can think of markets much like a dinner party. All of the brightest minds in finance are there—Nobel prize winners, traders who have been at their desk for 40 years, giant hedge fund managers. To trade against such an intelligent and motivated crowd, you would need very strong evidence—maybe even information that is currently unknown. The challenge and cost of finding and using such information very often negates the economic advantage the information provides.

But why not *use* this dinner party crowd? If we acknowledge the wisdom of such a crowd, it makes sense to use them to our advantage! We could, for example, ask their collective opinion on various future outcomes. As it turns out, the research literature has already begun to study this idea.

The development of options theory has provided investors with a way to understand the price for things like time (theta), underlying price change (delta), and risk (implied volatility), and the rise of a robust options market has allowed for the price discovery of such items. With a robust and active derivatives market we can, in effect, read the market's expectations for things that we care about, like future volatility. When managing the risk/return tradeoff, information about future risk is half the equation! This assumption, however, requires an efficient derivatives market. Because market efficiency is the default assumption of investors today, we offer only one study of options market efficiency to support this premise: Stein [1989] who finds that, while option markets do tend to slightly overreact short term, they are on the whole informationally efficient.

As it happens, the research on the informational content of derivative markets is fairly definitive. Frijns, Tallau and Tourani-Rad [2009] find that implied volatility (IV) does carry significant information about future asset volatility and return, a result echoed by Goyal and Saretto [2008]. In contrast, Bali and Hovakimian [2007] find that IV does not offer much predictive power for future asset returns, but it does offer predictive power for future volatility, a result echoed by Ammann, Skovmand, and Verhofen. Poon and Granger [2003] further find that IV was a better predictor for future volatility than historical volatility in three-quarters of the studies they surveyed.

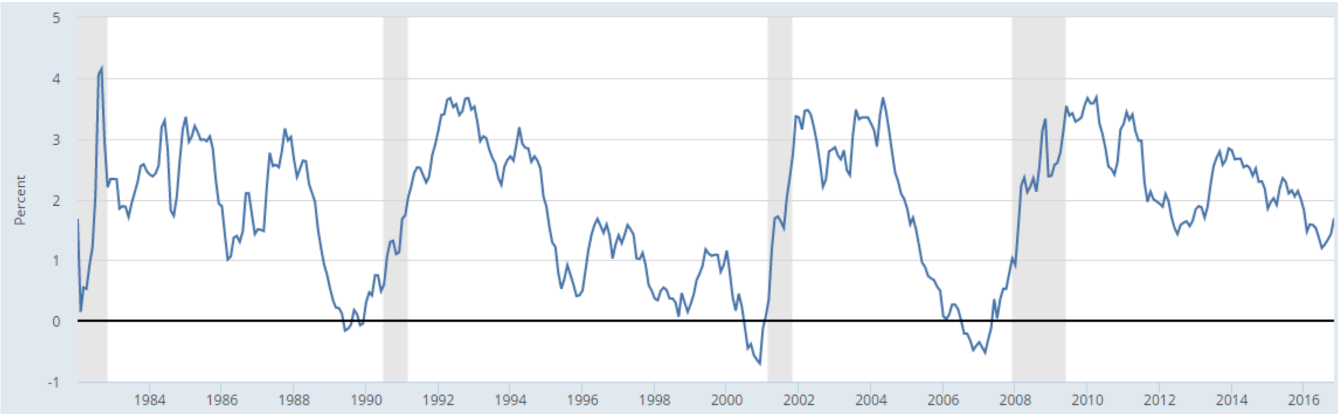
It would appear that derivative markets *do* offer predictive power, at least for future risk. This idea is furthered by Mostowfi and Stier [2013] along with Miao and Dunis [2005], who both offer a mean-variance optimization and/or risk-control scheme which incorporates the forward-looking information of implied volatility. Both schemes outperformed their benchmarks over the given test period. Given the theoretical and empirical evidence, it seems reasonable to conclude that this information can be used to the benefit of investors. We turn now to information about future returns.

While the literature is not silent on using markets to predict future returns, it is not quite so direct. Leaving aside much of the behavioral work and focusing only on the work which assumes efficient markets, we find that markets are—for the most part—able to foresee coming storms. The challenge, of course, is not in foreseeing a coming storm, but recognizing it *before* prevailing prices account for this expectation.

Empirical work done, such as that by Ranson [2016], has shown that certain asset prices tend to be first-movers and strong indicators of pending regime changes—a further indication of the power of market-driven predictions. The yield curve is also a well-known and widely followed indicator, empirically we can see this in Exhibit 2. Resnick and Shoesmith [2002] have even presented a stand-alone strategy for using a yield curve indicator to enter and exit stocks. Their work has the advantage of out-of-sample robustness, as 2007 through 2009 was not in their sample yet followed the pattern they identified.

The approach presented here takes a simple tack. Without expecting the yield curve to predict asset returns, this approach assumes it is indicative of recessionary/expansionary regimes only. Coupled with an understanding of asset returns within these two regimes, this allows a very simple mechanism for assessing future asset returns.

Exhibit 2: The Yield Curve as a Predictor of Recessionary Environments
10-Year US Treasury minus the 3-Month US T-Bill
shaded areas indicate recessions, source: Federal Reserve Bank of St. Louis



PUTTING IT ALL TOGETHER: A GOALS-BASED, ACTIVE ALLOCATION APPROACH

Armed with firm theoretical footing, we can now piece these disparate theories into one cohesive whole, beginning with the goals-based optimization scheme. In essence, the approach is to understand risk not as standard deviation, but as the probability of failing to achieve a goal. Reward, in turn, is redefined as the return achieved over-and-above the minimum required to fund a goal. We then aim to minimize the probability of goal-failure, and maximize the returns over-and-above the minimum. Mathematically, we understand this as:

$$\min \Phi\left(r_{req.} \,\middle|\, R\,, \sigma \right) \tag{1}$$

$$\max\ (R - r_{req.}) \tag{2}$$

where $r_{req.}$ is the annual return required to achieve a goal, R is the expected return of the portfolio, σ is the standard deviation of the portfolio, and $\Phi(\cdot)$ is the cumulative distribution function[1], which measures the percentage of possible returns which fall below $r_{req.}$. The portfolio optimization objective is to adjust the weights of given assets so that equations (1) and (2) are satisfied.

But this is a backward-looking approach, and the goal here is to incorporate forward-looking information. To understand where the theory enumerated above fits, we need to break down the variables. We begin with our understanding of portfolio standard deviation—note that standard deviation is NOT how we define risk in a goals-based setting. We understand σ as:

$$\sigma = \sqrt{\sum\sum w_i w_j \sigma_i \sigma_j \rho_{ij}} \tag{3}$$

where w_i is the proposed weight of asset i, w_j is the proposed weight of asset j, σ_i is the standard deviation of asset i, σ_j is the standard deviation of asset j, and ρ_{ij} is the historical correlation of asset i to asset j. By replacing historical standard deviation figures with implied volatility (which is forward looking), we can account for the market's expectation of future standard deviation. So, replacing σ_i with V_i and σ_j with V_j where V is the implied volatility of a given asset, then:

$$\sigma = \sqrt{\sum\sum w_i w_j \boldsymbol{V_i V_j} \rho_{ij}} \tag{4}$$

[1] To clarify the notation of the cumulative distribution function that we use here:
$\Phi(\, x \mid \mu \,, \sigma \,) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} \frac{e}{\sigma}^{-(x-\mu)^2 / 2\sigma^2}$

which is the standard deviation formula which should be used in equation (1). Recall, the information we propose incorporating is information about future volatility, which has been highlighted in this equation.

To incorporate information about future return, we turn to the findings of Resnick and Shoesmith [2002]. They show that the US Treasury yield curve from 10-months ago has predictive qualities for economic environments, specifically we use the 10-Year US Treasury minus the 3-Month US T-Bill. Exhibit 3 lays out their recession probability findings. Notice that as the spread compresses and inverts, recession probabilities increase. Though their study is over a decade old, their data has the advantage of being accurate out-of-sample, and we therefore see no reason to reinvent the wheel. There is one exception—we looked in the historical data for recessionary *market* environments, rather than strictly *economic* environments.

Exhibit 3: Bear Market Probabilities Based on the Yield Curve from 10 months Ago

Probability	Percentage Points of Spread
0%	> 2.54
10%	2.54 to 1.38
20%	1.38 to 0.55
30%	0.55 to (0.17)
40%	(0.17) to (0.83)
50%	(0.83) to (1.5)
60%	(1.5) to (2.21)
70%	(2.21) to (3.05)
80%	< (3.05)

We then used these recessionary market environments to develop an understanding of how various asset classes behave during those environments. Exhibit 4 displays the historical returns of the asset classes we tested in the two market environments. We incorporated TBills in our tests, however to compensate for the bias of the historical data, and to prevent time-travel bias, we used the previous calendar year TBill yield as the yield expectation for the year in which a test occurs.

Exhibit 4: Asset Returns in Recessionary and Non-Recessionary Environments
1968 – 2006

	S&P 500	Gold	20-Yr US Treasuries
Non-Recessionary	16.24%	8.04%	(0.05%)
Recessionary	(11.60%)	18.21%	2.48%

In order to account the recession/non-recession probability implied by the market, we must re-think the portfolio return definition somewhat. Equation (5) shows the result of this re-thinking:

$$R = (1 - \boldsymbol{P}) \cdot \sum w_i m_i + \boldsymbol{P} \cdot \sum w_i n_i \qquad (5)$$

where P is the yield-curve implied probability of a recessionary environment, w_i is the proposed weight of a given asset, m_i is the return of a given asset in a non-recessionary environment, and n_i is the return of a given asset in a recessionary environment. In short, the portfolio expected return can be thought of as the probability-adjusted sum of returns. As before, we have highlighted the information carrier set by the market. As an example:

suppose the yield spread from 10-months ago was 0.25 percentage points. Using Exhibit 3, we could infer the probability for a recessionary environment was 30%. Coupled with the return expectations of Exhibit 4 and equation (5), an equal-weighted portfolio (25% weight to each asset) would have an annualized return expectation of 6.92%.

Equation (5) and equation (4) can now be substituted into equations (1) and (2). For ease of reference, we have done this with equations (6) and (7):

$$\min \Phi\Big(r_{req.} \,\Big|\, (1-P)\cdot \sum w_i m_i + P \cdot \sum w_i n_i \;, \sqrt{\sum \sum w_i w_j V_i V_j \rho_{ij}} \Big) \tag{6}$$

$$\max \; ([(1-P)\cdot \sum w_i m_i + P \cdot \sum w_i n_i] - r_{req.}) \tag{7}$$

$$\text{subject to:} \quad \sum w_i = 1 \text{ and } 0 \le w_i \le 1 \tag{8}$$

Notice that equation (8) is the standard no-short-sale and no-leverage constraints. Because this investigation is aimed at goals-based investors (for whom short-sales and leverage are usually excluded), we did not test the removal of these constraints.

We should, perhaps, pause here to recap how this optimization scheme is constructed.

1. **First**, **a goals-based understanding of risk** (and thus optimization) **is used**. This approach advocates the use of phi (Φ), which measures the probability of goal-failure, as the primary metric for risk.
2. **Second**, **we have incorporated implied volatility as the market's future expectation for volatility** (standard deviation). This allows the optimization scheme to account for the forward-looking nature of the market.

3. **Third, we use the yield curve coupled with historical asset returns in recessionary and non-recessionary environments to generate expectations for future asset returns**. The study on which this thesis is based infers that the information content of the yield curve is lagged by 10-months. Therefore, we use yield curve information from 10-months ago as our indicator.
4. **Fourth, we blend all of this into an optimization scheme which is updated/rebalanced monthly**. The inputs and subsequent asset allocation are updated monthly using the market's expectation for future risk and return, in context of the investor's goal.

TALK (AND THEORY) IS CHEAP: *DOES IT WORK?*

For our proof-of-concept test, our investible universe was four assets: S&P 500, Gold, 20-Year US Treasuries, and 3-Month T-Bills. Serving as benchmarks (control tests), we used a passive portfolio optimized using historical data. Variance, return, and correlation data were updated annually, and we conducted a monthly walk-forward test beginning January 2007 and ending December 2015 (9 calendar years).

Our test portfolio was optimized monthly using the scheme presented in the previous section. Implied volatility and recession probabilities were updated monthly, whereas historical correlations were updated annually. Again, a monthly walk-forward test was performed.

In an attempt to rule out a possible statistical anomaly, we tested three different portfolios over the same time period: a 4% required return, a 6% required return, and an 8% required return. To determine which approach yields better goal-achievement probability, we further tested each portfolio over various rolling time periods: 36-month, 60-month, and 84-month.[2] This yielded a total of nine time-series tests.

For each actively allocated portfolio, the procedure was:

1. Input the four-week average implied volatility figure, calculated on the last trading day of the month, into the covariance table.
2. Input the yield-curve information from 10-months ago, which is translated into a recessionary probability.
3. Asset correlations are updated at the end of each year tested.
4. Optimize allocation monthly to minimize phi (Φ).
5. Updated allocations are then used to calculate a growth rate for the given month.
6. Repeat procedure for the 108 months tested.

The procedure for the passive portfolio tests was similar, but historical data was used rather than the forward-looking data we propose:

1. Build covariance tables using historical monthly correlations and standard deviations.
2. Optimize allocation at the beginning of the year to minimize phi (Φ).

[2] For clarification: one 36-month rolling time period would be 01/01/2007 to 12/31/2009, another 36-month rolling time period would be 02/01/2007 to 01/31/2009, etc.

3. Rebalance the portfolio to the target allocation (which was determined in step 2) every month.
4. Update covariance tables at the end of each year.
5. Re-optimize using updated historical data, and repeat procedure through the coming year.

Ultimately, the figure by which we must judge the approach is the actual probability of achieving a goal. We have certainly included other metrics, such as beta, alpha[3] and Sharpe ratios, but goal-based investors ultimately care about achieving their goals. Goal achievement is the *only* metric which matters to them, it should, therefore, be the only metric that matters to us as practitioners. Nonetheless, we also present more traditional metrics in an effort to help judge the relative benefit of this approach.

Exhibit 5: Test Results

		PASSIVE				ACTIVE								
2007 - 2015 Monthly Walk-Forward Tests		Goal Acheivement Frequency	Average Annualized Return	Annualized Standard Deviation	Sharpe Ratio	Average Change in Monthly Return (basis points)	Average Annualized Return	Annualized Standard Deviation	Sharpe Ratio	Alpha over Passive	Beta over Passive	Change in Efficiency	Goal Acheivement Frequency	Change in Goal Acheivement Freq. (percentage points)
4% Rreq.	36 Month	0%											30%	30.14
	60 Month	0%	1.13%	2.76%	0.32	10.25	2.36%	4.76%	0.45	0.83	1.45	38%	27%	26.53
	84 Month	0%											0%	0.00
6% Rreq.	36 Month	64%											100%	36.00
	60 Month	61%	5.10%	13.07%	0.37	52.15	11.35%	14.15%	0.79	6.77	0.89	111%	100%	39.00
	84 Month	28%											100%	72.00
8% Rreq.	36 Month	59%											97%	38.00
	60 Month	53%	5.21%	13.38%	0.37	64.05	12.90%	14.80%	0.85	8.52	0.83	130%	98%	45.00
	84 Month	16%											100%	84.00

[3] For the purposes of this discussion we use Jensen's [1967] alpha: $\alpha = r_i - \left(r_f + \beta_{i,m}\left(r_m - r_f\right)\right)$ where r_i is the return of the investment portfolio, r_f is the risk-free rate (we used the average risk-free rate in our comparisons), $\beta_{i,m}$ is the investment portfolio's beta relative to the market (or benchmark portfolio), and r_m is the return of the market (or benchmark portfolio). For ease of presentation, we have multiplied alpha by 100.

A look through Exhibit 5 illustrates the success of this approach—at least over the most recent market cycle. As Parker [2014] shows, drawdowns can wreak havoc on impending goals, we have therefore decided to begin the test in 2007—at the most inopportune time for a goals-based investor.

Nonetheless, by all metrics measured, the incorporation of the market's expectations increases returns and/or decreases risks. In all three return requirements, the actively allocated portfolio generated alpha—in two of three cases, alpha was in excess of 6.0. Furthermore, the actively allocated portfolios greatly increased portfolio efficiency (as measured by Sharpe ratios)—in two of three cases, the active portfolio *more than doubled* the efficiency of the passive portfolio.

Judging the procedures by which investors judge our procedures, we find that the active portfolios increase an investor's ability to achieve goals in eight out of nine tests, with one test resulting in no change. In all, the average increase in goal achievement probability is 41 percentage points. That is the difference between achieving goals 31% of the time and 72% of the time—a *very* significant difference for investors!

We also conducted hypothesis tests concerning the difference of average monthly returns. For the 4%, 6%, and 8% $r_{req.}$ portfolios, we wanted to determine whether the increase in monthly returns over the passive portfolio was statistically significant. Our null hypothesis was that the mean difference of monthly returns was less than or equal to zero (H_0: $\mu_d \leq 0$ versus H_a: $\mu_d > 0$), which, if rejected, would indicate that the active portfolio is statistically superior in average monthly return to the passive portfolio. For the 8% and

6% $r_{req.}$ portfolios, we were able to reject the null in favor of the alternative at the 5% level of significance. However, for the 4% $r_{req.}$ portfolio, we were unable to reject the null at the 5% level of significance. Therefore, we are led to conclude that the procedure does not increase monthly returns in a statistically significant way for the 4% $r_{req.}$ portfolio, but the average increase in monthly return *is* statistically significant for the 6% and 8% $r_{req.}$ portfolios.

Due to the nature of the optimization scheme, the 8% $r_{req.}$ is comparable to the S&P 500 in terms of expected return and volatility. As a further robustness test, we conducted a direct comparison of the active portfolio to the S&P 500. In an effort to factor out the effects of diversification through the 2007-2009 downturn, we also present the passive portfolio. Exhibit 6 illustrates the result of this comparison.

Exhibit 6: Strategy Comparison to the S&P 500

	S&P 500	8% Active	8% Passive
Annualized Return	5.39%	12.90%	5.21%
Standard Deviation	16.05%	14.80%	13.38%
Sharpe Ratio	0.32	0.85	0.37
Treynor Ratio	0.05	0.22	0.06
Beta to S&P 500	1.00	0.57	0.77
Alpha Over S&P 500	-	9.70	1.01
Max Monthly Drawdown	(18.05%)	(17.64%)	(17.95%)

A look through Exhibit 6 shows that this approach is indeed superior to a buy-and-hold of the S&P 500. Our test results indicate that an investor can expect an extra 62 basis points *per month* of return from this strategy over the S&P 500. And, because the Sharpe ratio of the active portfolio is considerably higher than the S&P 500, the investor is gaining this return with proportionally less risk. Furthermore, when benchmarked to the S&P 500, this strategy generated alpha of 9.70!

We conducted another hypothesis test to determine if this monthly excess return over the S&P 500 was statistically significant. Again, our null hypothesis was that the monthly average difference in return was less than or equal to 0, while our alternative hypothesis was that the return difference was greater than 0 (H_0: $\mu_d \leq 0$ versus H_a: $\mu_d > 0$). We were able to reject the null in favor of the alternative at the 5% significance level. This would indicate that the excess return over the S&P 500 is statistically significant.

Of course, some of these benefits may simply be garnered from the effects of diversification. The passive portfolio, however, should account for those benefits. Recall, we found that the excess returns of the active portfolio over the passive portfolio were statistically significant. Therefore, it is reasonable to conclude that the active allocation strategy is superior to a buy-and-hold strategy on the S&P 500, and that this effect must be attributable to the incorporation of market-driven expectation information.

Goals-based investing is exceptionally path-dependent. So, though it is only one path, we have further illustrated the growth of $1 from January 2007 through December 2015 for each portfolio tested (Exhibit 7). In all cases, the ending value of the actively allocated portfolio is significantly higher than the passively allocated portfolio. In fact, the ending value of the 4% $r_{req.}$ actively allocated portfolio is $1.22 versus $1.10 (11% higher, Panel A); the ending value of the 6% $r_{req.}$ actively allocated portfolio is $2.53 versus $1.46

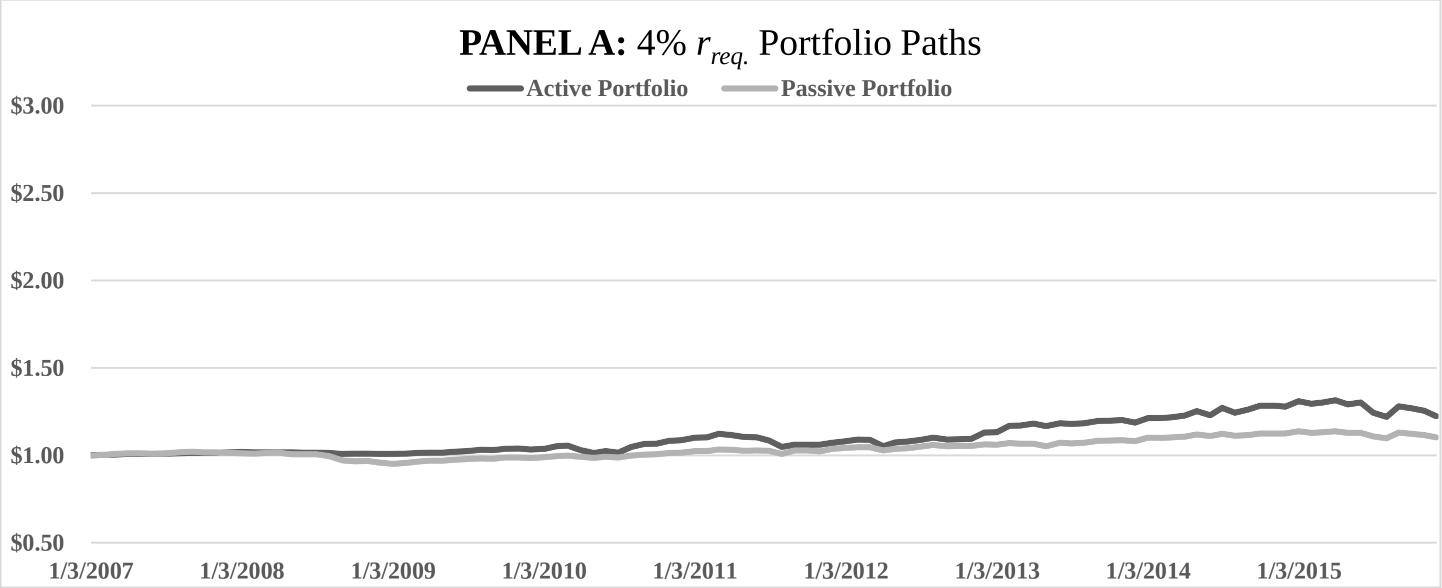
(73% higher, Panel B); and the ending value of the 8% $r_{req.}$ actively allocated portfolio is \$2.88 versus \$1.47 (95% higher, Panel C).

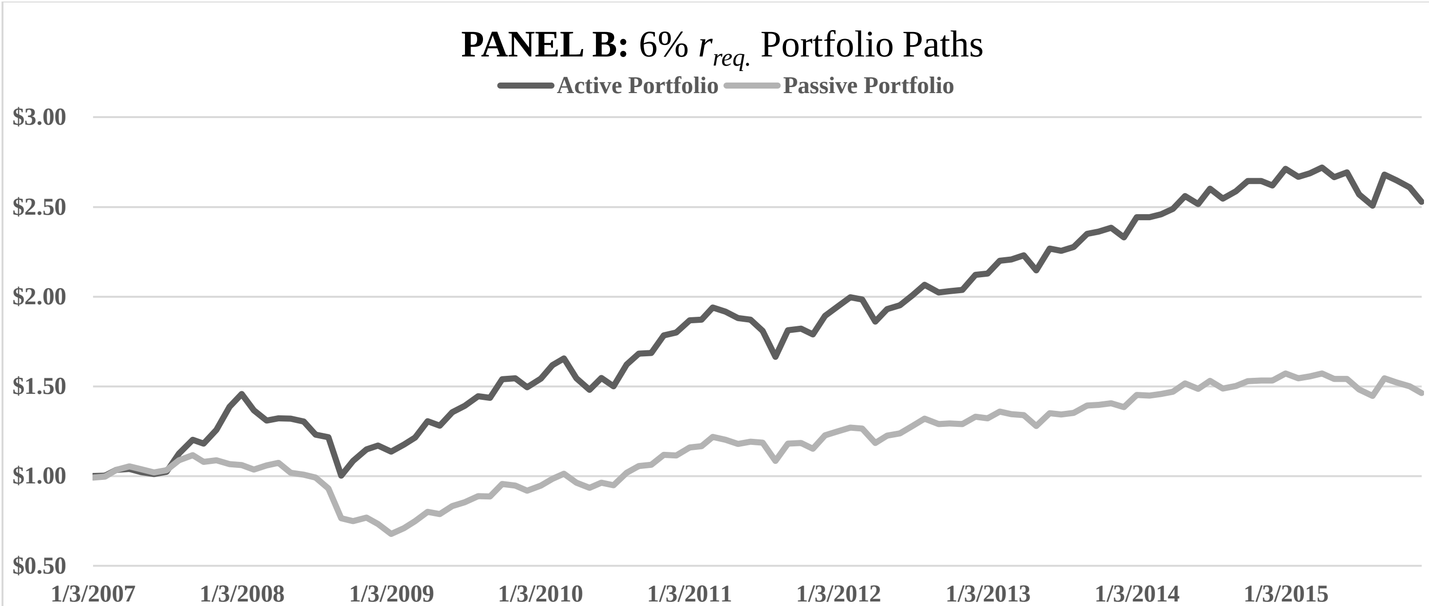
Also of note is the result of the S&P 500 buy-and-hold approach versus the actively allocated 8% $r_{req.}$ strategy (Panel D of Exhibit 7). \$1 invested in the S&P 500 in January 2007 grew to \$1.44 by the end of 2015. In contrast, \$1 invested in the active allocation strategy grew to \$2.88 over the same period. That is a difference of 100%. Put differently, an investor would have *double* the amount of wealth if they had utilized this strategy over a simple buy-and-hold of the S&P 500 during the period of 2007 – 2015.

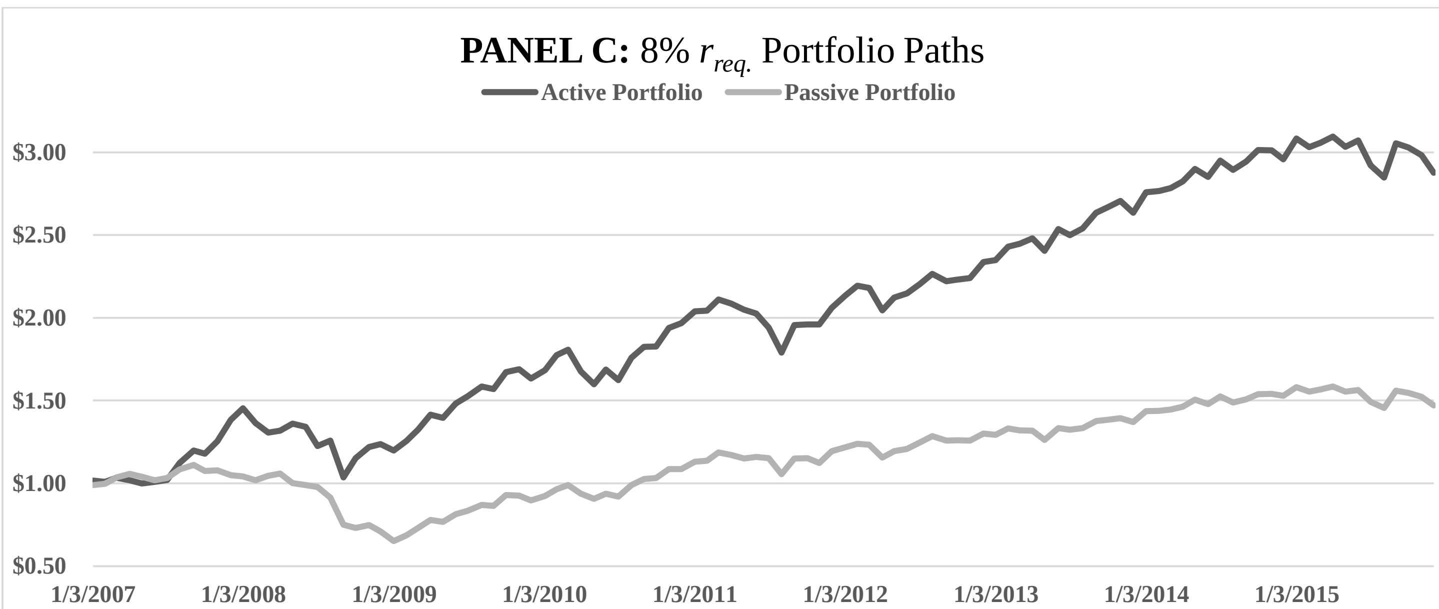
It does seem reasonable to conclude that the procedure proposed here can legitimately be expected to generate higher levels of wealth over passive strategies.

Exhibit 7: Growth of \$1 for Various Portfolios

Active versus Passive, 2007 through 2015




PANEL B: 6% $r_{req.}$ Portfolio Paths
Active Portfolio
Passive Portfolio
$3.00
$2.50
$2.00
$1.50
$1.00
$0.50
1/3/2007
1/3/2008
1/3/2009
1/3/2010
1/3/2011
1/3/2012
1/3/2013
1/3/2014
1/3/2015


PANEL C: 8% $r_{req.}$ Portfolio Paths
Active Portfolio
Passive Portfolio
$3.00
$2.50
$2.00
$1.50
$1.00
$0.50
1/3/2007
1/3/2008
1/3/2009
1/3/2010
1/3/2011
1/3/2012
1/3/2013
1/3/2014
1/3/2015

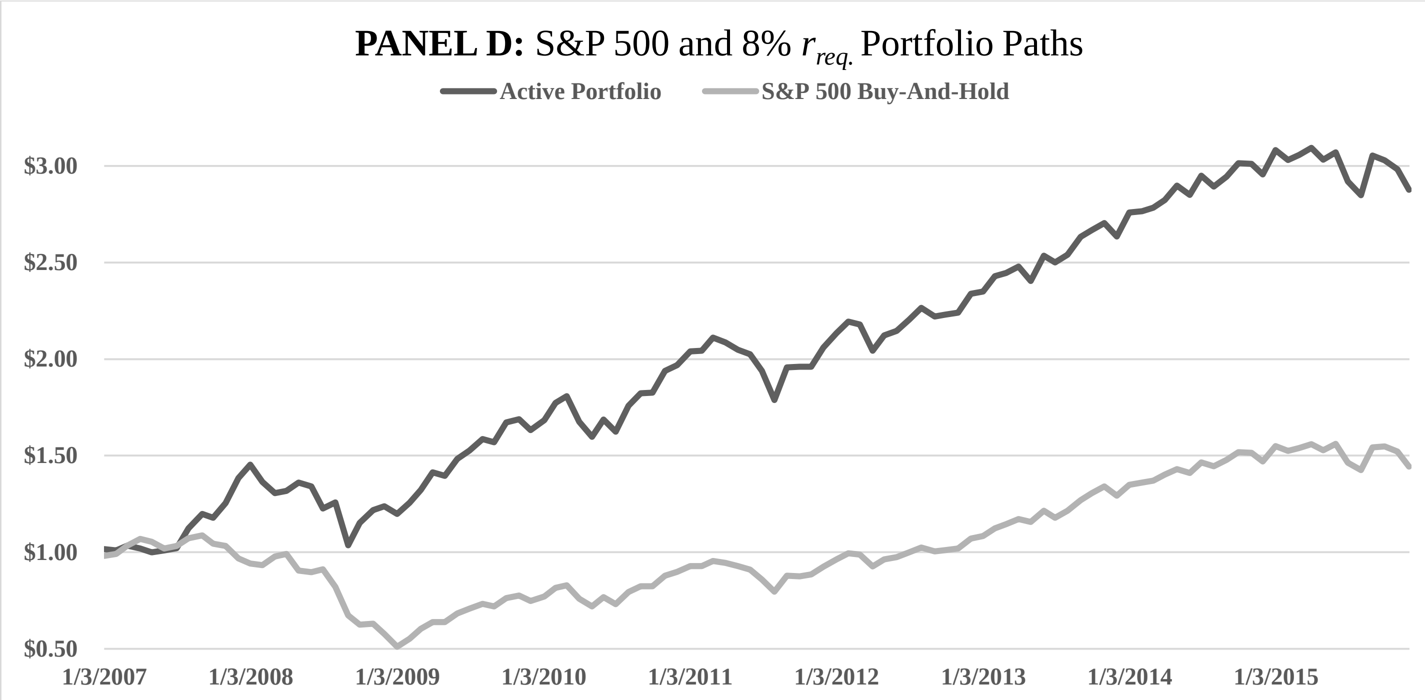
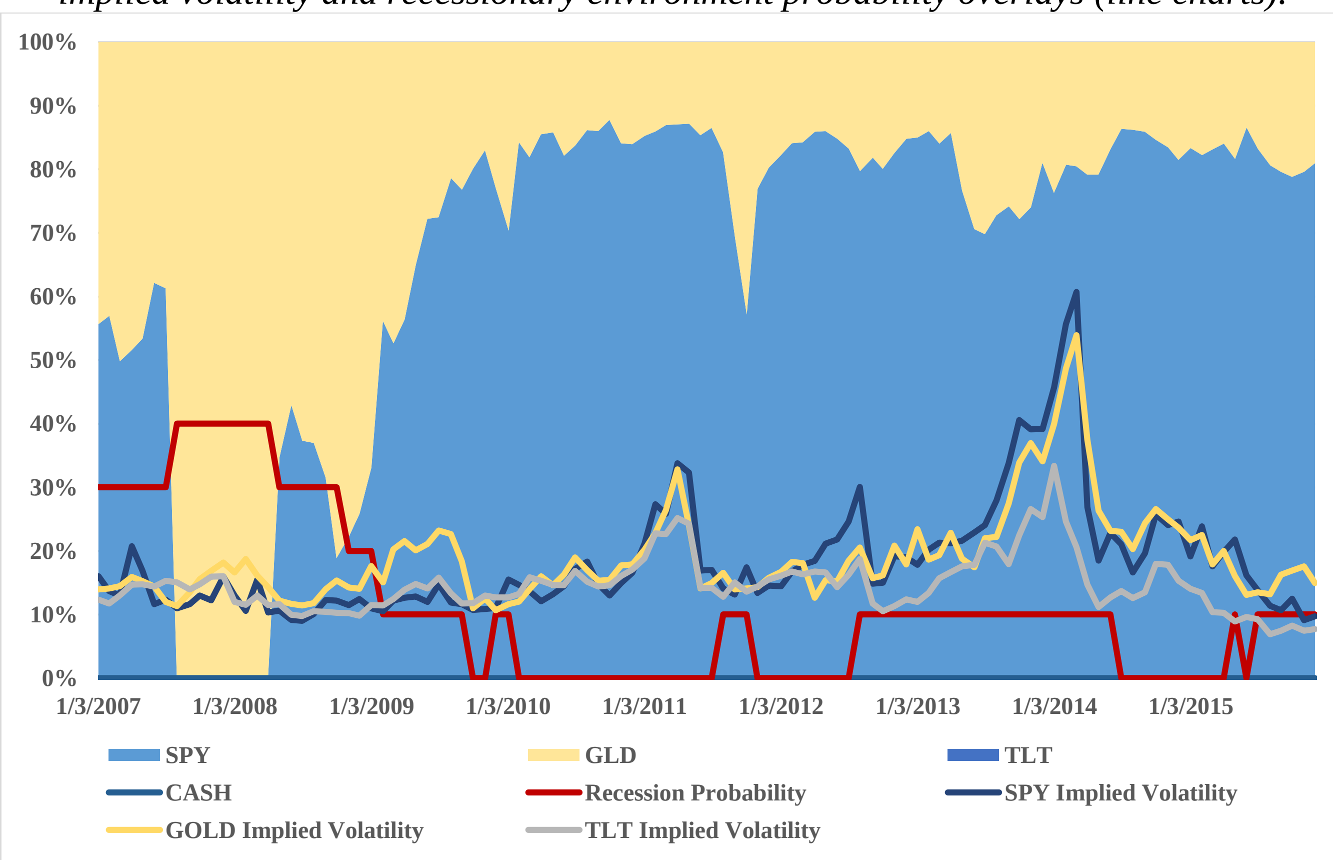


Exhibit 8: Dynamic Monthly Allocations Example

6% $r_{req.}$ Portfolio – *monthly asset allocation (area chart) with implied volatility and recessionary environment probability overlays (line charts).*



SOME CLOSING THOUGHTS

The difficulty in measuring the value of active investing is well known in the industry. Furthermore, many researchers have concluded that active management cannot be reasonably expected to deliver consistent alpha, pointing to market efficiency (and empirical evidence) as the primary rationale for that premise. We turn that argument around.

If markets are indeed efficient (or at least mostly so), then the risk and return projections of markets should incorporate all publically-available information, and should be a fair and reasonable estimate of future outcomes. We can, therefore, use market expectations as a basis for managing a risk/reward tradeoff, and thus generate alpha.

Our statistical tests confirm that we have reasonable basis to accept that the average monthly returns of the active strategy presented here are superior to those of the passive strategy, and superior to a simple "buy-and-hold the S&P 500" strategy. Furthermore, we have shown how taking an active approach can give investors higher probabilities of achieving their goals. At the end of the day, this is the metric we care about because this is the metric investors care about.

Yet we cannot discount the importance of the theoretical support for this approach. After all, without a firm understanding of *why* something works, we cannot be certain that it will continue to work into the future. Furthermore, without a firm understanding of the "whys," we cannot know which marketplace changes might cause the strategy to stop working. Both of these could leave us vulnerable and potentially chasing a strategy which has ceased to work because of some third thing to which we are blind. Keeping a vigilant eye on the relative efficiency of markets and being wary of overreactions would be key to the continued success of this strategy (see Thaler [2015] and Barberis and Thaler [2003]).

Due to the difficulty of collecting historical implied volatility data, our tests were limited to the 2007 to 2015 period. However, because that period incorporates a significant market downswing as well as subsequent rally, we would expect these results to be robust across market cycles.

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