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THE PROFITABLE DIVIDEND YIELD STRATEGY

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Stocks with high dividend yield (DY) have value-like returns and defensive qualities that make them highly attractive to investors. We show that this investment strategy can be powerfully enhanced by choosing stocks with both high DY and high gross profits-to-assets (GPA). Consistent with the predictions of the clean surplus accounting model, high-GPA stocks have high average returns despite their relatively low book-to-market ratios (Novy-Marx, 2013). Profitable firms are also less prone to distress than unprofitable firms. The resulting Profitable Dividend Yield (PDY) strategy inherits the defensive nature of high-DY stocks, while providing superior average returns than either standalone strategies. Bootstrap simulations show that the PDY delivers superior long-term outcomes.

1 Introduction

If the goal of investment is to accumulate wealth over the long term, dividend-paying stocks have much to recommend. Dividend-payers have higher average monthly returns than non-dividend-payers even though they are less volatile. Moreover, dividend-payers outperform non-dividend-payers in declining markets (Fuller and Goldstein, 2011), making them appealing to loss-averse investors (Kahneman and Tversky, 1979; Benartzi and Thaler, 1995).

In this paper, we show that an even more powerful solution for long-term wealth accumulation is to select stocks with both high dividend yield and high gross profits-to-asset (high-GPA). We call this strategy, the Profitable Dividend Yield strategy, or PDY for short.

Why combine GPA with dividend yield? From a philosophical viewpoint, the PDY strategy makes sense because high dividend yield and high-GPA stocks have value-like returns despite different book-to-market characteristics. The clean surplus version of the dividend discount model implies that holding book-to-market ratio constant, stocks with higher expected profits have higher expected returns (Fama and French, 2006). Novy-Marx (2013) argues that current earnings or income

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before extraordinary items used by Fama and French (2006) does not cleanly measure a firm's true economic productivity and has little predictive power for future earnings in contrast to GPA. Consistent with this intuition, he shows that stock returns are strongly and positively related to GPA in the cross-section, after controlling for standard risk factors. Interestingly, high-GPA firms outperform low-GPA firms in terms of both raw and risk-adjusted returns even though they have lower book-to-market ratios. In other words, high-GPA firms produce superior returns not because they are value stocks but because they are "good" growth stocks.

High-GPA firms also enhance the pure dividend yield strategy in other ways. In particular, firms that are profitable today tend to remain profitable many years into the future as shown by Novy-Marx (2013) and Asness *et al.* (2014). Novy-Marx also finds that high-GPA are less prone to distress, have long cash flow durations and lower leverage than unprofitable firms. These characteristics of high-GPA firms are another motivation for our PDY strategy. Adding GPA as a stock selection criterion therefore helps mitigate concerns that high dividend yield firms are more exposed to distress risk or are mostly mature firms with low future earnings prospects (Fama and French, 2001, 2006).

We show that the PDY strategy inherits the low-risk nature of high dividend yield stocks in bad market states (periods of negative market returns), and exhibits markedly superior average returns in good market states. Consequently, PDY has a higher unconditional mean return (1.46% per month) compared to 1.07% individually for high dividend yield and high-GPA stocks. It also outperforms the standalone strategies on a risk-adjusted basis, with a Sharpe ratio of 0.70 and a highly significant three-factor alpha of 0.46% per month (5.52% annualized).

Finally, we use simulations to examine PDY as a long-run investment strategy, assuming an investor has a 20-year holding period and framing our analysis as an asset allocation problem where the default portfolio is a standard 60/40 asset mix of the stock market index (60%) and long-term bonds (40%). We show that even allocating a small percentage of capital away from this default portfolio to PDY stocks yields significantly superior results in many performance dimensions such as mean cumulative return, shortfall risk, Omega ratio and prospect theory value function. Overall, these results indicate that the PDY strategy is a powerful contender to the traditional approach for long-term wealth accumulation.

The rest of this paper is organized as follows. Section 2 describes our data and portfolio formation methodology. Section 3 presents summary statistics showing the risk–return characteristics of the different investment strategies. Section 4 examines the performance of the PDY strategy in good and bad market states. Section 5 looks at the PDY strategy from the perspective of a long-term investor whose default asset allocation is a standard 60/40 stock/bond portfolio commonly recommended by financial advisers to young investors. This section uses simulations to examine whether a long-term investor can benefit by diverting some capital from the 60/40 portfolio to PDY. Section 6 concludes with a summary of this paper's key findings.

2 Data and methodology

The sample period for this study is from June 1963 to December 2013. Our stock universe comprises all ordinary common stocks traded on the New York Stock Exchange (NYSE), American Stock Exchange (Amex) and Nasdaq, from the Center for Research on Security Prices (CRSP). Following the literature, we only include stocks with share codes 10 and 11, thus excluding REITS, financials, foreign shares, ADRs, and closed-end

funds. We remove stocks that have market capitalizations in the bottom quarter to exclude the most illiquid stocks that are too costly to trade for any reasonable volume. Stocks with prices below $5 are also eliminated to mitigate microstructure effects such as the bid–ask bounce which is associated with low-priced stocks (Jegadeesh, 1990). Data on stock prices and dividends are from CRSP. Accounting data are from Compustat.

Each year, we sort stocks into quintiles based on their gross profits-to-assets (GPA) and dividend yield and consider value-weighted returns. We use GPA instead of earnings off the income statement based because as pointed out by Novy-Marx (2013), gross profit is uncontaminated by marketing expenses, research and development expenses, interest payments, and other items unrelated to true economic profitability. Gross profit is computed as Total Revenue (REVT) minus Cost of Goods Sold (COGS), where the latter measures all expenses directly related to production. We define GPA as gross profits divided by book assets (AT). We use book assets rather than book equity since GPA is an asset-level measure of productivity. Since Compustat data starts in 1962, GPA for fiscal year 1962 is applied to the first portfolio sort at the end of June 1963. Empirical tests for this sort subsequently cover the period from July 1963 through June 1964. We repeat this process every year to generate data through December 2013.

Dividend yield is computed as the ratio of dividends paid over the 12 months prior to the formation date to the stock price at the formation date. Following Naranjo *et al.* (1998), we exclude stocks with either a missing dividend yield or an unsustainable yield, defined as an annual yield of 24% or more.

The following notations will be used to denote the quintile portfolios: G1 (G5) is the quintile with the lowest (highest) GPA and D1 (D5) is the quintile with the lowest (highest) dividend yield. Following Christie (1990), we designate D1 as the zero-dividend yield portfolio as this portfolio has large disparities in terms of firm size and risk-adjusted returns compared to the lowest non-zero-dividend yield portfolio, D2. We also form blended portfolios using stocks at the intersection of the GPA and dividend yield quintiles. We focus on G5D5 which consists of stocks in the highest GPA and dividend yield quintile.

3 Risk and return of the profitable dividend yield strategy

Table 1 reports firm characteristics (stock price, firm size, book-to-market ratio, dividend yield, and leverage) and risk–return statistics of the following quintiles: G1, D1, G5, D5, and two intersection portfolios: G5D5 and G1D1. Panel A reports the time series averages of the characteristics for each portfolio. Firm size is in millions of dollars. BM is book-to-market ratio, dividend yield is in percent per year and leverage is the ratio of total liabilities to total liabilities plus firm market equity. We see that G5 (highly profitable firms) are large growth firms with low BM ratios, low leverage, and low dividend yield, while unprofitable firms (G1) display opposite characteristics. These differences accord with the intuition that profitable firms are less prone to financial distress than unprofitable firms. Panel A also shows that D1 firms display the characteristics of growth firms—low BM ratios, low dividend, yield and low leverage, while D5 exhibits value-like characteristics. The PDY strategy which invests in G5D5 is motivated precisely by the concern that high dividend yield stocks may have higher distress risk than low-yield stocks.

Panel B reports risk–return statistics of each quintile. G1 earns the lowest average excess returns of 0.47% per month. The other individual portfolios have similar average excess returns of between 0.66% and 0.69% per month. D5 is the least

Table 1 Descriptive statistics.

	Gl	Dl	G5	D5	G1D1	G5D5
Panel A						
Price	26.65	22.53	30.59	29.49	15.31	24.63
Size ($ millions)	2,059	1,100	2,673	4,006	950	3,521
BM	0.79	0.62	0.52	0.86	0.60	0.64
DY (% per year)	2.99	0.08	1.64	5.50	0.00	4.70
Leverage	0.51	0.35	0.27	0.53	0.40	0.35
Panel B						
Excess returns	0.47	0.69	0.66	0.67	0.72	1.04
Std deviation	4.57	7.26	4.72	3.74	7.52	5.17
Sharpe ratio	0.35	0.33	0.48	0.62	0.33	0.70
Panel C						
Nominal end wealth ($)	8.98	12.73	27.28	36.98	13.26	242.76
Real end wealth ($)	1.19	1.69	3.63	4.92	1.77	32.31
GM	4.5	5.2	6.8	7.5	5.3	11.6

This table reports descriptive statistics of portfolios formed by sorting stocks based on their gross profits-to-assets (GPA) and dividend yield (DY). The sample period is from July 1963 to December 2013. Eligible stocks are sorted each month based on their GPA in the previous fiscal year and trailing 12-month dividend yield, assigned into quintiles based on NYSE breakpoints and rebalanced yearly. All portfolios are value-weighted. G1 (G5) denotes the quintile with the lowest (highest) GPA firms. D1 (D5) denotes the quintiles with the lowest (highest) dividend yield. G5D5 is the portfolio comprising firms in the highest dividend yield and GPA quintiles. Panel A reports time series means of firm characteristics for the average firm for each portfolio. Panel B reports mean excess returns (over the one-month T-bill rate), standard deviation of monthly returns, and the Sharpe ratio. Panel C reports the nominal and real value of $1 invested in 1963 as of December 2013. Real values are computed assuming a constant inflation rate of 4% per annum. GM denotes the geometric return corresponding to nominal end wealth. Returns in Panel B are in percent per month. Geometric mean returns in Panel C (GM) are in percent per annum.

volatile portfolio, consistent with the defensive nature of high dividend yield stocks, while D1 is the most volatile. These risk–return patterns translate to a much higher Sharpe ratio for D5 than D1 (0.62 versus 0.33). G5 also has a higher Sharpe ratio than G1. This is mainly due to its higher average excess return (1.04%) compared to that of G1, in line with the prediction of clean surplus accounting.

The PDY portfolio (G5D5) displays outstanding performance compared to its univariate counterparts. Its average excess return of 1.04% per month is 55% higher than that of G5 and D5. While G5D5 is also more volatile than G5 and D5, as we shall see later, much of this volatility is actually "good volatility" in the sense that G5D5 outperforms its component portfolios by more in bad times than it underperforms them in good times. Averaged over the full sample, G5D5 has a remarkably high Sharpe ratio of 0.70, demonstrating the return synergy that comes from blending high-GPA stocks with high dividend yield stocks. For perspective, the Sharpe ratio of the market

portfolio (the CRSP value-weighted stock index) is 0.38, while the Sharpe ratio of G5 and D5 does not exceed 0.62.

G5D5 is a counter-example to the popular notion that taking high risk is the only way to earn high average returns. Moreover, its high Sharpe ratio indicates that it is an attractive portfolio for investors with long investment horizons. This benefit can be seen retrospectively in Panel C. The row labeled "Nominal End Wealth" reports the value (in excess of the T-bill rate) as of end December 2013 from $1 invested in July 1963. The row below it reports the terminal wealth adjusted for inflation of 4% per year, close to the average CPI inflation rate over the sample period (Federal Reserve, 2014). Over the 50 years to December 2013, a dollar invested in G5D5 increased to $32.31 in real terms, well above the real terminal value for G5 ($3.63) and D5 (($4.92). The last row reports the geometric mean return of each portfolio based on nominal wealth. Consistent with the terminal wealth rankings, none of the portfolios come close to the G5D5's geometric return of 11.6% per annum.

Readers may wonder whether the PDY strategy works just as well with other definitions of profitability. To investigate this question, we consider the following alternative definitions of profitability: (i) return on assets (ROA), (ii) return on equity (ROE), accruals (ACCR), and cash flows-to-assets (CFA). For ROA and ROE, profit is measured by net income before extraordinary items as in Fama and French (2006). ACCR is motivated by large literature beginning with Sloan (1996) showing that accruals are inversely related to future profitability. We measure accruals as depreciation minus changes in working capital. Piotroski (2000) and Griffin and Lemmon (2002) show that proxies for net cash flows are positively related to future stock returns. We define CFA as net income plus depreciation minus changes in working capital and capital expenditures scaled by total assets. To avoid data mining, we rank stocks based on the average of all four profitability measures after standardizing each measure so that they have zero mean and unit standard deviation. We then construct P5D5, an intersection portfolio analogous to G5D5 but using the new profitability measure (denoted by the prefix P). The key result is that P5D5 is inferior to G5D5 in all performance dimensions. The mean excess return of P5D5 is 0.58% per month (G5D5: 1.04%), its Sharpe ratio is 0.47 (G5D5: 0.70), and its geometric mean return is 6% per annum (G5D5: 11.6%). P5D5 also has positive but much smaller CAPM and three-factor alphas than G5D5 (details available on request). These results are consistent with Novy-Marx's (2013) finding that gross profits is a more powerful predictor of future profitability and cash flows than other commonly used earnings measures.

4 Returns over market states

One of the appeals of dividend-paying stocks is that they tend to outperform non-dividend-paying stocks in declining markets (Fuller and Goldstein, 2011). Table 2 shows that G5D5 inherits this insurance characteristic. Panel A (B) reports the returns of the different portfolios in bad (good) market states. We define good and bad states using four market return indicators and a broad-based economic indicator. The market indicators for the good state are: positive market excess returns (positive MKT) and the best 5%, best 10%, and best 25% for MKT. Similarly, the market indicators for the bad state are: negative MKT, and the worst 5%, worst 10%, and worst 25% for MKT.

We use monthly readings on the Chicago Fed National Activity Index (CFNAI) to measure the state of the economy. The CFNAI is a weighted average of 85 indicators of economic activity and inflationary pressure.[1] The 85 indicators are drawn from four broad categories of data: (a)

Table 2 Returns in different market states.

	Returns relative to MKT (percent)					
	MKT	Gl	G5	Dl	D5	G5D5
A. Bad states						
MKT < 0	−3.6	0.3	0.4	−1.8	1.6	1.5
MKT worst 5%	−10.3	0.6	0.7	−3.8	3.6	3.4
MKT worst 10%	−8.2	0.5	0.6	−3.7	3.2	3.1
MKT worst 25%	−5.2	0.3	0.6	−2.5	2.0	2.0
CFNAI < 0	0.4	0.0	0.3	0.2	0.4	1.2
B. Good states						
MKT > 0	3.4	−0.2	0.0	1.6	−0.8	−0.1
MKT best 5%	9.3	−0.4	0.2	4.6	−2.2	−1.6
MKT best 10%	7.8	−0.4	0.0	3.4	−1.7	−1.4
MKT best 25%	5.7	−0.2	0.1	2.6	−1.3	−0.5
CFNAI > 0	0.5	0.0	0.0	0.1	0.0	0.1

This table reports average excess returns of portfolios sorted by gross profitability-to-assets and dividend yield in good and bad states. See Table 1 for a descriptive of each portfolio. We define a bad state as one where either: (a) the market excess return is negative, (b) the market excess returns are in the left tails (specifically, the worst 5%, 10%, and 25%) of the historical distribution, or (c) the economy is in contraction (a negative value for the Chicago Fed National Activity Index (CFNAI). We define a good state using opposite values for these indicators. All returns are shown as monthly percentages. The numbers in the MKT column are the average excess returns for the market portfolio. The numbers in the other columns are average of the returns of each portfolio minus those of the market.

production and income, (b) unemployment and hours, (c) personal consumption and housing, and (d) sales, orders, and inventories. The CFNAI is standardized to have zero mean and a unit standard deviation so that a positive index reading indicates that the economy is growing above trend and a negative index reading corresponds to growth below trend. We classify periods with positive (negative) values of the CFNAI as periods of economic expansion (economic contraction).

The column labeled MKT reports the average market excess returns in each state. The other columns report the average returns of the portfolios relative to the market. Panel A shows that G5D5 outperforms the market in bad times. For example, in periods when MKT < 0, the monthly excess returns of G5D5 is on average 1.5% higher than the market excess returns. G5D5 is even more defensive during the most stressful periods (the worst 5% to worst 25% scenarios). It also retains this defensive quality in bad economic times as shown in the last row of Panel A. Finally, Panel B shows that while G5D5 underperforms the market in good times, this underperformance is of a smaller magnitude than its outperformance in good times.

5 Simulation analysis of long-run returns

The benefits of high-return, low-risk strategies like G5D5 are best displayed when their returns are compounded over many periods because the geometric mean return is positively correlated

with the Sharpe ratio. In this section, we explore how the returns–synergy of G5D5 plays out for investors with long investment horizons. Historical returns provide some perspectives on this issue. As we saw earlier, the annualized geometric mean return of G5D5 is 2.8% higher than that of D5, and that this modest return difference implied a very big disparity in cumulative returns over the sample period (cf. Table 1, Panel C). But historical data is inherently limiting for the study of long-term returns because even with a century of data, there are only 10 independent decade-long return histories. To overcome the limitations of historical data, we use block bootstrap simulations to generate hypothetical long-horizon returns.

The block bootstrap method introduced by Knusch (1989) is an improvement over the classical bootstrap for identically and independently distributed (IID) data introduced by Efron (1979). The idea behind the block bootstrap method is to divide the data into overlapping blocks, then randomly "stitch" the selected blocks to generate new data. An important advantage of block re-sampling is that it enables us to mimic the same dependence structure as the original data within the blocks, whatever that structure may be. Large sample properties of the block bootstrap have been extensively studied in the statistics literature.[2] Hansson and Persson (2000) and Fong and Koh (2015) are recent applications of the block bootstrap method in finance.

We apply the block bootstrap methodology to portfolios formed by combining G5D5 with traditional stock–bond portfolios, where the stock component is represented by the market portfolio. We use this framework to study the long-run performance of G5D5, assuming the investor has a 20-year horizon.

Our baseline assumption is a 60/40 portfolio, with 60% of funds invested in the stock market index, and 40% in 20-year Treasury bonds. We then simulate buy-and-hold cumulative returns for this baseline portfolio and for portfolios that combine the 60/40 and G5D5 portfolios in different proportions. At one extreme, all funds are invested in the 60/40 portfolio, and at the other extreme, all funds are invested in the G5D5 portfolio. We examine other combinations in intervals of 10%.

Throughout, we use a block size of 60 months to simulate 20-year returns 1,000 times. Specifically, we form overlapping blocks of returns of length 60 months using the original data, randomly re-sample these blocks with replacement 1,000 times and "stitch" them to form long-horizon returns of 20 years. The choice of a 60-month block size follows Hansson and Perrson (2000), and is a compromise between the desire for a sufficiently large block to capture time dependencies in stock returns and the need for a large number of overlapping blocks to generate long-run returns.

For each replication, we compound the simulated monthly returns into 20-year terminal wealth assuming that $1 is invested at the beginning. We then compute various performance measures to assess the distribution of terminal wealth. These include (a) percentiles of terminal wealth, (b) shortfall risk, defined as the percentage of terminal wealth below a target terminal wealth, (c) the Omega ratio (Keating and Shadwick, 2002), defined as the ratio of average upside returns to average downside risk, and (d) mean and median values of the prospect theory value function to assess long-run performance from the viewpoint of loss-averse investors (Kahneman and Tverksy, 1979). We use returns of 4% and 6% per annum to define target terminal wealth for the Omega ratio and value function analysis. Details of prospect theory as used in this paper are provided in the Appendix.

Table 3 Bootstrap simulations of 20-year holding period returns for different combinations of the 60/40 (stock/bond) portfolio and the G5D5 portfolio.

Performance Measure	% in G5D5					
	0%	20%	40%	60%	80%	100%
A. Cumulative returns ($)						
Mean	5.7	10.8	15.8	20.9	25.9	31.0
Median	5.1	8.8	12.6	16.1	19.8	23.3
l0th percentile	2.3	3.7	4.9	5.9	7.0	8.1
90th percentile	10.1	20.5	31.0	41.4	52.3	62.7
			4% Target			
B. Target-based performance						
<Target	87	19	8	3	1	0
Omega ratio	0.76	10.00	52.10	390.41	5,174.21	—
PT value function						
Mean	2.84	6.39	9.62	12.69	15.66	18.56
Median	2.55	5.26	7.86	10.17	12.45	14.62
			6% Target			
C. Target-based performance						
<Target	238	69	32	14	9	4
Omega ratio	0.13	1.41	6.02	19.14	54.13	133.23
PT value function						
Mean	1.80	5.59	8.89	12.01	15.01	17.92
Median	1.74	4.54	7.18	9.51	11.82	14.00

This table reports long-term performance statistics based on 1,000 simulation runs for various combinations of the 60/40 stock/bond portfolio and the G5D5 portfolio. The 60/40 portfolio has a weight of 60% in the CRSP value-weighted stock index and 40% in 20-year Treasury bonds. G5D5 is the portfolio formed from the intersection of high gross profits-to-assets stocks (G5) and high dividend yield stocks (D5). The header row shows the percentage allocated to G5D5. The raw data for the simulations are monthly portfolio returns from July 1963 to December 2013. A moving block bootstrap with a block size of 5 years is used to simulate 20-year cumulative returns. Panel A reports selected percentiles of cumulative returns, assuming $1 is invested at the start of the sample period. Panel B (C) reports the percentage of simulations where the cumulative return is below that implied by a target return of 4% (6%) per annum, the Omega ratio, computed as the average of returns above the target return divided by the average of returns below the target return, and the median and median values of the prospect theory value function with $\alpha = 0.88$ and $\lambda = 2.25$ as in Tversky and Kahneman (1992).

Table 3 reports our bootstrap simulation results. The top row shows the portfolio weight for G5D5: "0%" means that all funds are invested in the 60/40 portfolio throughout the 20-year period, "20%" means that 20% of funds are invested in the G5D5 portfolio with the rest in the 60/40 portfolio, and so on. The PDY strategy corresponds to 100% invested in G5D5 (last column).

Panel A displays the mean, median, 10th, and 90th percentiles of the simulated 20-year holding period returns. Cumulative returns are monotonically increasing in the percentage invested in G5D5. In fact, a 100% allocation to G5D5 generates the highest cumulative returns not only on average but also across all percentiles, as exemplified by the 10th and 90th percentiles. These results indicate that the PDY strategy stochastically dominates over the 60/40 strategy. They also suggest that G5D5 is likely to perform well in other dimensions. This is confirmed in Panel B which reports statistics that explicitly capture downside risk relative to a target of 4% per annum. Specifically, we report the number of 1,000 simulated returns that fall short of the target cumulative return, Omega ratio, and the mean and median values of the prospect theory value function with loss-aversion parameter (λ) equal to 2.25.

G5D5 is the best-performing strategy for all the downside risk measures. It has the lowest shortfall risk, highest Omega ratio, and largest mean and median values for the prospect theory value function. The worst-performing strategy is the 60/40. The difference in performance between these two strategies is so large that even a small allocation of 20% to G5D5 leads to a marked reduction in shortfall risk and substantial improvements in Omega ratio and average value functions. Panel C shows that these results are robust to a higher (6%) target return. As expected, mean value functions are now lower than under a 4% target. However, this decrease is much smaller for G5D5 (−3.4%) than for the 60/40 portfolio (−37%). This finding also holds for the median value function. As a further robustness check, we repeat our analysis for an investor with a loss-aversion parameter of $\lambda = 5.5$, holding the target return at 6%. The results (not reported) show that little is changed by doubling the loss-aversion parameter. G5D5 continues to be the optimal strategy.

6 Conclusion

High dividend yield stocks appeal to many investors. In this paper, we show that profitability is a powerful complement to high dividend yield in driving stock returns, profitable firms are less prone to distress, profitability is strongly persistent, and high profitability implies high expected returns given book-to-market values in accord with the clean surplus accounting model. Consistent with these characteristics, we show that the PDY strategy invested in D5G5 stocks inherits the defensive nature of high dividend yield stocks in bad times, while underperforming the market only modestly in good times. Averaged over market states, the strategy yields higher average returns and markedly higher Sharpe ratios and geometric mean returns than either of the standalone (D5 and G5) strategy. Finally, we show that the strategy also performs well in simulations across various performance dimensions.

Appendix. Prospect theory value function

This appendix briefly reviews the functional form of the original value function proposed by Kahneman and Tversky (1979) in their experimental study of loss aversion, and describes how we compute value functions using our simulated returns.

Let W denote terminal wealth, R the reference point, and $X = W - R$ relative terminal wealth. The original form of the value function proposed by Kahneman and Tversky (1979) is:

$$V(X) = X^{\alpha} \qquad \text{if } X \geq 0,$$
$$V(X) = -\lambda(-X)^{\alpha} \qquad \text{if } X < 0,$$

where V is the value function defined over X, α measures the curvature of the utility function and λ is the loss aversion parameter. $\alpha < 1$ implies that individuals are risk averse over gains and risk seeking over losses, and $\lambda > 1$ implies that individuals are loss-averse. Tversky and Kahneman

(1992) estimate α and λ to be 0.88 and 2.25, respectively. We report simulation results using $\alpha = 0.88$ and two values for λ: 2.25 and 5.5.

The reference point is another key parameter in Prospect Theory. The reference point may be the status quo such as current wealth or a desired level of future wealth. Since we are interested in long-horizon returns, a reasonable reference point is a target level of future wealth. Since we are interested in the performance of the D5D5 strategy vis-à-vis that of traditional stock–bond strategies, we use as reference points, target returns for these strategies based on reasonable long-term forecasts for inflation, stock returns and bond returns. Specifically, we use the consumer price index (CPI) to measure inflation and assume future inflation rates of 4%, close to the median inflation rate over the sample period. Recent yields on long-term Treasury bonds reflect investors' expectations of low inflation going forward. Following Dimson *et al.* (2013), we use the 20-year Treasury bond yield at the end of 2013 (3.7%) as our forecast of the average real return for long-term Treasury bonds. Dimson *et al.* (2013) propose 3–3.5% as reasonable estimates of the real geometric average return for global stock markets. We use their upper forecast of 3.5% as our estimate future real equity returns for the U.S. Overall, these assumptions imply nominal return forecasts of between 4.3% and 6.1% depending on the stock–bond mix. We therefore set target returns of 4% and 6% a year to assess the performance of the various investment strategies.

Notes

[1] Compiled by the Federal Reserve Bank of Chicago, the CFNAI is normally released towards the end of each calendar month.

[2] See Lahiri (1991, 1992) for early work on the asymptotic properties of block bootstrap estimators. Jing (1997) shows that the block bootstrap performs well both at the center and tails of distributions. Calhoun (2011) proves that block bootstrap methods consistently estimate the distribution of the sample mean under weak dependencies and moment conditions.

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