

Reducing Sequence Risk Using Trend Following and the CAPE Ratio

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The risk of experiencing bad investment outcomes at the wrong time, or *sequence risk*, is a poorly understood but crucial aspect of the risk investors face—particularly those in the decumulation phase of their savings journey, typically over the period of retirement financed by a defined contribution pension scheme. Using US equity return data for 1872–2014, we show how this risk can be significantly reduced by applying trend-following investment strategies. We also show that knowing a valuation ratio, such as the cyclically adjusted price-to-earnings (CAPE) ratio, at the beginning of a decumulation period is useful for enhancing sustainable investment income.

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The topic of pension savings and decumulation is of growing importance in many parts of the world as companies retreat from defined benefit schemes, leaving investment and withdrawal decisions to individuals. Some economists have focused their attention on this important topic by proposing ever more creative accumulation and decumulation strategies. These strategies include frameworks for combining deferred annuities, state benefits, and guaranteed annuity-type income, along with flexible income from investments of varying degrees of risk. These approaches, however, are generally silent on the type of investment strategy needed for a successful accumulation and decumulation experience with risky assets. Instead, they tend to create risk-free benchmarks of index-linked bonds (see Sexauer, Peskin, and Cassidy 2012). In our view, designing a savings and decumulation strategy without giving careful consideration to investment strategy is like designing all the necessary elements of a car—chassis, gearbox, braking system, and so on—except the engine.

In this article, we attempt to shift the focus back to investment strategy—that is, the risk engine. In our study, we used the concept of perfect withdrawal rates (Suarez, Suarez, and Walz 2015) to investigate the post-1872 decumulation experience of a US investor with a 20-year investment horizon. We also sought to explain and highlight the potentially pernicious effect of the sequence of investment returns—known as *sequence risk*—when investors withdraw regular income from their investments. We found evidence to suggest that applying a simple trend-following filter to an equity investment can help generate returns with low drawdowns, which reduces sequence risk and leads to enhanced *perfect withdrawal rates* (PWRs). Another question that we addressed in our study is whether indicators of equity market valuation are useful for predicting withdrawal rates at any point in time. For instance, does a high cyclically adjusted price-to-earnings (CAPE) ratio imply an overvalued market followed by equity price falls and a bad sequence of returns, leading to lower PWRs? We found clear evidence to suggest that the CAPE ratio can be used to help enhance withdrawal rates.

Withdrawal Rates

The literature on optimal withdrawal rates in retirement can be traced to Bengen (1994) and his concept of “the 4% rule.” He showed that a 4% withdrawal rate from a retirement fund, adjusted for inflation, is *usually* sustainable for “normal” retirement periods. Using overlapping samples of historical stock and bond returns, Cooley, Hubbard, and Walz (1998, 1999, 2003, 2011) confirmed that conclusion with similar findings.

A crucial distinguishing feature of these studies is that they rely on a constant real withdrawal amount throughout the decumulation phase, with no “adaptive” behavior as circumstances change. A number of studies have introduced adaptive rules. Guyton and Klinger (2006) manipulated the inflationary adjustment when return rates are too low, modifying the withdrawal amount, whereas Frank, Mitchell, and Blanchett (2011) used adjustment rules that depend on how much the rate of return deviates from historical averages. Zolt (2013) similarly suggested reducing the inflationary adjustment to the withdrawal amount in order to increase the portfolio’s survival rate, as appropriate. Thus, these withdrawal rates “adapt” to changing circumstances.

An important extension of this research is to treat the planning horizon length as a stochastic (instead of fixed) variable. The aim (quite sensibly!) is to ensure that the funds in the retirement account “outlive” the retiree: Stout and Mitchell (2006) used mortality tables to make sure that the uncertain retirement period was considered, whereas Stout (2008) decreased the withdrawal amount whenever the account balance fell below a measure of the present value of the withdrawals yet to be made and increased it when the balance was above this measure. Mitchell (2011) similarly used thresholds to initiate such adjustments.

A more theoretically coherent approach treats the selection of withdrawal amounts as a lifetime-utility maximization problem. Milevsky and Huang (2011) considered the total discounted value of the utility derived across the entire retirement period, where the length of retirement is a stochastic variable and the subjective discount rate is a given. Williams and Finke (2011) used a similar model with more realistic portfolio allocations.

Blanchett, Kowara, and Chen (2012) focused on a different concept. They measured the relative efficiency of different withdrawal strategies by comparing each

strategy’s actual cash flows with the flows that would have been feasible under perfect foresight; in other words, they used the concept of a “perfect withdrawal rate.” This perfect withdrawal rate is the withdrawal rate that effectively exhausts wealth at death (or at the end of a fixed, known period), which could be identified if one had *perfect foresight* of all returns over that period. It can, therefore, be used as a benchmark for comparing competing investment strategies and for deriving a measure of a crucial risk faced by investors who draw income from investment portfolios: sequence risk, or the risk of experiencing bad investment outcomes at the “wrong” time. Typically, the *wrong time* is toward the *end* of the accumulation phase and at the *beginning* of the decumulation period; that is, it is symmetrical around the date of retirement. Blanchett et al. (2012) and Suarez et al. (2015) constructed a probability distribution for the PWR, using it to derive a new measure of sequence risk in the process. In this article, we use these ideas to show that a particular class of investment strategies (both simple and transparent) that tends to smooth returns can offer superior perfect withdrawal rates across practically the whole range of return environments. It is this smoothing of returns that leads to a better decumulation experience for virtually all investing time frames.

Calculating PWRs and Deriving a Measure of Sequence Risk

For any given series of annual returns, there is one and only one constant withdrawal amount that will leave the desired final balance on the account after n years (the planning horizon). This number is known as the *perfect withdrawal amount* (PWA). It can also be expressed as a percentage relative to the initial value of the investment pot, in which case it is referred to as the PWR. The final balance could be a bequest or indeed could be zero. In the case of the latter, Suarez et al. (2015) pointed out that identifying the PWR is equivalent to finding the fixed payment that will fully pay off a variable-rate loan after n years.

The basic relationship between account balances in consecutive periods is

$$K_{i+1} = (K_i - w)(1 + r_i), \quad (1)$$

where K_i is the balance at the beginning of year i , w is the yearly withdrawal amount, and r_i is the annual rate of return percentage in year i . Applying Equation 1 chain-wise over the entire planning horizon (n years),

we obtain the relationship between the starting balance, K_S (or K_1), and the ending balance, K_E (or K_n):

$$K_E = \left(\left[(K_S - w)(1 + r_1) - w \right] (1 + r_2) - w \right) (1 + r_3) \dots - w (1 + r_n). \quad (2)$$

And we solve Equation 2 for w to obtain

$$w = \left[K_S \prod_{i=1}^n (1 + r_i) - K_E \right] / \sum_{j=1}^n (1 + r_j). \quad (3)$$

Equation 3 calculates the constant amount that will draw down the account to the desired final balance if the investment account provides, for example, a 5% return in the first year, 3% in the second year, -6% in the third year, and so on, or any other particular sequence of annual returns. This constant amount is the PWA.

Quite simply, if one knew in advance the sequence of returns that would come up in the planning horizon, one would compute the PWA, withdraw that amount each year, and reach the desired final balance exactly and just in time.

Numerous studies provide examples of a sequence of, say, 30 years of returns generated, possibly with reference to a historical period or via Monte Carlo simulations—and offer the unique solution of the PWA. The PWA involves withdrawing the same amount every year, giving the desired final balance—with no variation in the income stream, no failure, and no surplus. As we have noted, Blanchett et al. (2012) presented a measure similar to PWA called the *sustainable spending rate* (SSR). Suarez et al. (2015) pointed out that the PWA is a generalization of SSR, with SSR being the PWA when the starting balance is \$1 and the desired final balance is zero.

So, every sequence of returns is characterized by a particular PWA or PWR, and hence the retirement withdrawal question is really a matter of “guessing” what the PWA will (eventually) be for each retiree’s portfolio and objectives. Therefore, the problem becomes how to estimate the probability distribution of PWAs from the probability distribution of the returns on the assets held in the retirement account.

Note that the analysis thus far offers several useful insights into sequence risk measurement. First, Equation 3 can be restated in a particularly useful way because the term $\prod_{i=1}^n (1 + r_i)$ in the numerator is simply the cumulative return over the entire retirement period (R_n).

The *denominator*, in turn, can be interpreted as a measure of sequence risk:

$$\begin{aligned} \sum_{i=1}^n \prod_{j=i}^n (1 + r_j) &= (1 + r_1)(1 + r_2)(1 + r_3) \dots (1 + r_n) \\ &+ (1 + r_2)(1 + r_3) \dots (1 + r_n) + (1 + r_3)(1 + r_4) \dots (1 + r_n) \\ &+ \dots + (1 + r_{n-1})(1 + r_n) + (1 + r_n). \end{aligned} \quad (4)$$

The interpretation is straightforward. For any given set of returns, Equation 4 is *smaller* if the *larger* returns occur *early* in the retirement period and *lower* rates occur at the *end*, because the later rates appear more often in the expression. Suarez et al. (2015) suggested the use of the reciprocal of Equation 4 to capture the effect of sequencing. So, let

$S_n = 1 / \sum_{i=1}^n \prod_{j=i}^n (1 + r_j)$, which decreases as the sequence becomes more favorable. And even though one set of returns appearing in two different orders will have the same total return (i.e., R_n with different S_n values), the PWA rates will be different.

Normally, the financial analysis of investment returns focuses on *total* return and some reward-to-risk measure, such as the Sharpe ratio, that does not consider the return sequence—but in both accumulation and decumulation, the *order* of returns matters. Consider the three sets of returns reported in **Table 1**. Clearly, the mean, volatility, and Sharpe ratio (and even maximum drawdown) are the same in each case, but the returns’ sequences differ, as evidenced by the different values of sequence risk ($1/S_n$), with lower values associated with higher PWRs.

This finding allows a useful, highly intuitive simplification of Equation 3 into Equation 5. The PWA depends positively on the total return, R_n , starting amount, K_S , and measure of sequence risk, S_n , and depends negatively on the final amount, K_E :

$$w = (R_n K_S - K_E) S_n. \quad (5)$$

Table 1 and Equation 5 make clear that it is not simply the total return that matters but also the order in which the component returns occur: If “good” returns come early in the sequence, the PWA will be larger than if they occur later.

Other studies have tried to account for sequence risk (Frank and Blanchett 2010; Frank et al. 2011; Pfau 2014), often developing proxy variables to measure the correction required to address the sequencing issue. Suarez et al. (2015) suggested that Equation

Table 1. Example of Sequence Risk

Year	Return Set 1	Return Set 2	Return Set 3
1	20%	-20%	0%
2	10	-10	10
3	0	0	-10
4	-10	10	-20
5	-20	20	20
Mean	0.00%	0.00%	0.00%
Standard dev.	15.8%	15.8%	15.8%
Max. drawdown	-20.0%	-20.0%	-20.0%
$1/S_n$	3.98	5.98	4.92
PWR	23.87%	15.90%	19.30%

Note: This table shows the effect on sequence risk ($1/S_n$) and PWR of three series of returns that have the same arithmetic mean, standard deviation, and maximum drawdown.

5 comes directly from the simplest, most natural interpretation of the problem—namely, that S_n is not a proxy but, rather, a measure of what the authors termed *orientation* (return rates going up, going down, up a little, then down a lot, etc.), which is the crucial concept for assessing sequencing.

Finally, note that w (the PWA) can be transformed into a withdrawal rate by dividing Equation 5 by K_S :

$$w/K_S = R_n S_n - S_n (K_E / K_S). \quad (6)$$

Note that if we have a bequest motive, we simply need to know the fraction of the initial sum to be bequeathed to calculate the PWR. As Suarez et al. (2015) pointed out, in contrast to simplistic financial planning solutions, it is not necessary to set aside a bequest sum beforehand because these funds can also generate returns that may be used for consumption. Setting aside a sum is simply a special case of the general form expressed in Equation 6.

In this article, we use the concept of PWR to compare investment strategies over a 20-year decumulation horizon. Of course, not everyone will live for 20 years in retirement. Our analysis can be adapted for any withdrawal horizon. Furthermore, we are not suggesting that the strategies we examined in our study should provide retirees' only income source. On the contrary, they should be combined with, say, a deferred annuity that kicks in at the end of the chosen decumulation period (for a fuller discussion of

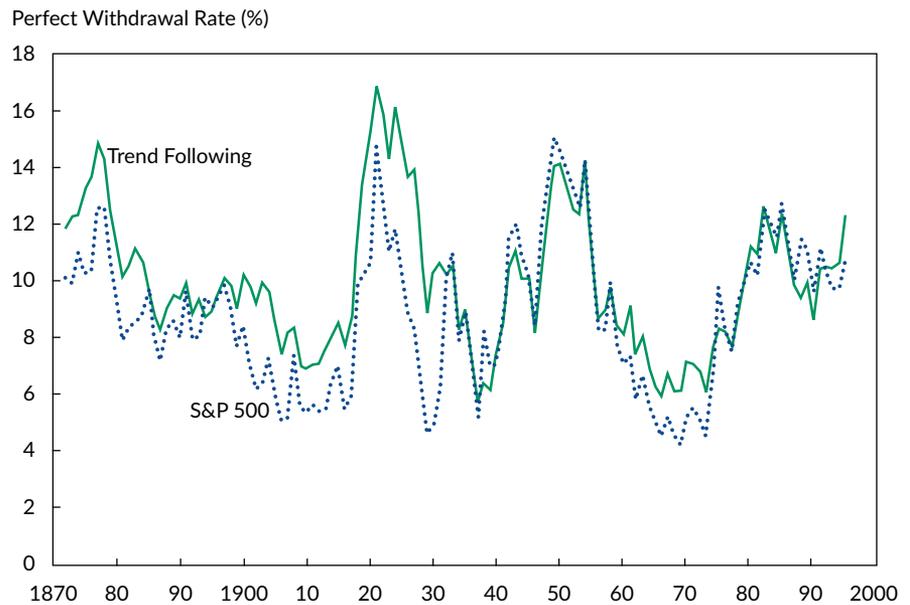
the potential benefits of this dual approach to funding one's retirement, see, e.g., Sexauer et al. 2012; Merton 2014).

Constructing a Probability Distribution for PWRs in an All-Equity Portfolio

Much of the financial planning literature aims to make probability statements regarding an investor's chance of running out of funds, given a particular withdrawal rate and planning horizon. Therefore, we can create a probability distribution for the PWR/PWA using a long run of monthly equity returns extracted from the Shiller website.¹ This all-equity portfolio may be considered rather unlikely as an investment choice in practice, but it serves to illustrate our key points regarding the choice of investment strategy. In practice, of course, investors may wish to hold a proportion in bonds and other asset classes to benefit from diversification and to align the investment portfolio's risk with their personal level of risk tolerance. A surprising result may well be that a 100% equity portfolio is not such a bad idea, *providing* that one overlays it with a trend-following filter.

If we had perfect foresight, what would the real PWR look like over time, assuming a 20-year decumulation period? **Figure 1** illustrates this scenario, in which (as throughout this article) we assume a zero-bequest intention. We focus here on the dotted line, which

Figure 1. Real PWR for 20-Year Decumulation with 100% US Stock Investment: With and without Trend Following

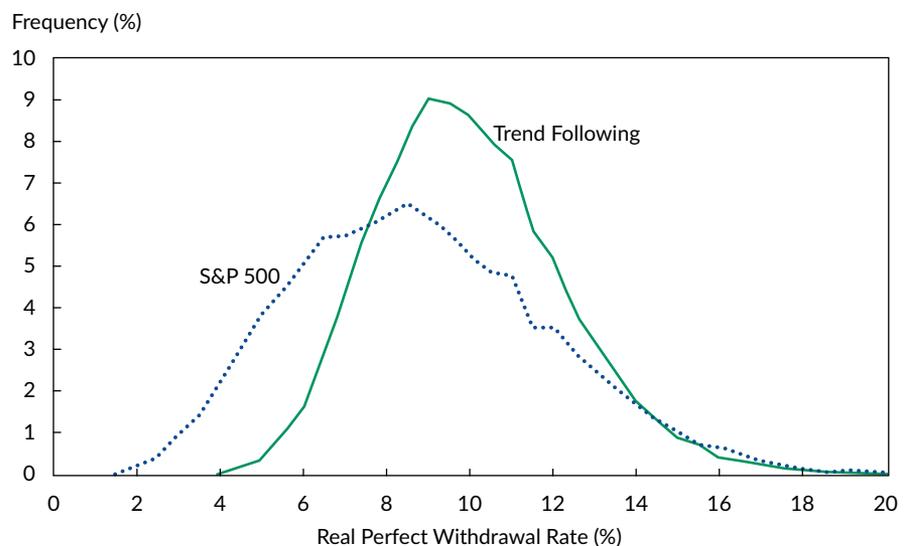


shows the PWR generally varying between 8% and 12% but occasionally straying as low as 4%, in 1930, and as high as 15%, in 1949. For several years in the 1980s, it is well above 10%. These results suggest two things. First, there is a huge variation in investors' ability to withdraw cash from a retirement pot, depending on one's birth date. Second, *all* the rates are above 4%, giving very long-term succor to Bengen's (1994) 4% rule (at least over 20-year periods).

Now that we know what the history of PWRs would look like with perfect foresight for the 100% S&P 500 portfolio, we can construct a probability distribution for this particular investment strategy. We

begin with 100% invested in this equity portfolio. We calculate the real returns on the S&P 500 Index for each year over 1872–2014. We then use Monte Carlo techniques to draw 20 years of returns, one at a time, with replacement. These sets of returns are then interpreted as the real returns over a 20-year investment horizon, in the order drawn, that an investor might experience. We repeat this process 20,000 times, allowing us to compute the cumulative return (R_n) and sequencing factor (S_n) for each series of returns, providing us with 20,000 (R_n, S_n) pairs. The dotted line in **Figure 2** represents the frequency distribution of the PWA formula (Equation 5) evaluated at each of these 20,000

Figure 2. PWR as Percentage of Initial Balance: 20,000 Simulations of 20-Year Decumulation Using Annual S&P Real Returns with and without Trend Following, 1872–2014



(R_n, S_n) pairs, using \$100,000 as a starting balance and \$0 as a desired terminal balance. The second column in Panel A of Table 2 contains the distribution's percentiles. Taken together, these results are broadly comparable with Figures 3 and 4 in Suarez et al. (2015), albeit with real PWRs and a 20-year investment horizon. We can interpret the distribution of PWRs as follows: There is a 1% chance of a real PWR of 2.95% or less, a 10% chance of a real PWR of 5.01% or less, and a 50% chance of a real PWR of 8.64% or more. Given that the final balance is \$0, any overshoot in withdrawing would result in ruin. Hence, we could say that 50% of the Monte Carlo withdrawal runs produced real PWRs of less than 8.64%, so the failure risk for withdrawing more than 8.64% is 50%. Similarly, the failure risk for withdrawing more than 5% a year is about 10% (i.e., 10% of the runs produced real PWRs of more than 5.01%).

The inverse of failure risk is surplus risk, which can be estimated by inverting the roles of PWR and the end balance. For a given end balance and PWR, we can say that a surplus accrues over a certain percentage of time, reflecting the occurrence of PWRs greater than the chosen PWR. In fact, in the Suarez et al. (2015) example, with a nominal perfect withdrawal amount of \$43,000 a year (i.e., a 4.3% withdrawal rule), 74% of the Monte Carlo runs end up with more money than they began with; in 58% of the runs, the final balance is double the starting balance, with a 12% probability of ending up with 10 times the initial sum.

Finally, in Panel B of Table 2 (column 2), we present descriptive statistics of the real buy-and-hold annual returns on the S&P 500 over this period—that is, descriptive statistics of the risk engine. Note in particular the very high maximum drawdown of 76.8%.

Table 2. Real PWR Percentiles as a Percentage of Initial Balance, 1872–2014

	S&P 500	S&P 500 with Trend Following
<i>A. Percentiles</i>		
1	2.95%	5.57%
5	4.20	6.61
10	5.01	7.21
20	6.11	8.03
30	7.00	8.67
40	7.85	9.23
50	8.64	9.80
60	9.43	10.38
70	10.38	11.01
80	11.47	11.81
90	13.05	13.00
95	14.37	14.04
99	16.87	16.22
<i>B. Statistics</i>		
Annualized real return	6.82%	8.84%
Annualized real volatility	14.29	9.86
Maximum real drawdown	76.8	34.88

Trend Following and Sequence Risk

Clearly, from Equations 5 and 6, the sequence risk measure, S_n , influences the PWR directly: Equation 6 shows that the more favorable sequencing, S_n , produces a higher PWR. More favorable sequencing is associated with relatively good returns early in the planning period (see Okusanya 2015). In particular, avoiding heavy losses in the early phases of decumulation is crucial for high PWAs. But if asset returns are unpredictable, how can we secure a favorable S_n ? Milevsky and Posner (2014) investigated how and when traded equity options can help reduce sequence risk and, in so doing, be used to extend the life of a retiree's investments. Another very straightforward solution, however, is to acknowledge that although the *order* of returns cannot be predicted, it may be possible to produce investment strategies that offer substantially reduced return volatility or, more precisely, a much reduced drawdown of returns, because reduced volatility in itself is insufficient to secure a high PWA. Indeed, although there is no precise mathematical relationship between maximum drawdown and sequence risk, we suggest that a low maximum drawdown should be associated in practice with more favorable sequence outcomes.

Diversifying across asset classes should nudge portfolio returns in the desired direction, with improved risk–return trade-off and possibly a lower maximum loss. But an even more powerful technique can be applied to individual asset classes, to dramatic effect: *trend following*, whereby one invests in an asset

when it is in an uptrend (defined as a current value above some measure of recent past average) and switches to cash when the current value is below such an average.² This approach to investing has been explored by a number of researchers in the past. Faber (2007) showed how this simple approach can be applied across a broad range of US asset classes as a disciplined way of implementing asset allocation decisions to produce multi-asset-class portfolios with higher returns and lower volatility.³ Ap Gwilym, Clare, Seaton, and Thomas (2010) also found that trend-following filters can enhance risk-adjusted returns. For example, they showed how the approach can halve the maximum drawdown on an investment in the MSCI World Index, compared with a simple buy-and-hold strategy, over 1971–2008. Hurst, Ooi, and Pedersen (2014) expanded the universe of asset classes considerably in their research into the properties of trend-following filters. They applied a trend-following filter to 24 commodity markets, 11 equity markets, 15 bond markets, and nine currency pairs, using data over 1903–2012. They found that the approach “delivered strong returns and realized a low correlation with traditional asset classes” over that period. Clare, Seaton, Smith, and Thomas (2013) found similar evidence using the S&P 500 and essentially concluded that the simple 10-month moving-average signal,⁴ also applied in this article, produces higher risk-adjusted returns than more complex technical rules, such as those relating to crossover points. They also concluded that any positive return enhancement applying such trend-following rules daily is almost always offset by higher transaction costs.

Our basic hypothesis, then, is that applying a simple, monthly trend-following rule to any series of asset returns dampens volatility, typically maintains or increases returns over long periods, and substantially reduces maximum drawdown for that series, which should in turn reduce sequence risk.⁵ To test this hypothesis, we replaced the buy-and-hold equity investment strategy with an equity strategy that incorporates a trend-following filter. To that end, we created a set of trend-following returns by using a 10-month moving average of the S&P 500. At the end of each month, if the index value is greater than its 10-month moving average, the investor earns the return on the S&P 500 in the subsequent month. If, however, at the end of the month, the index value is below its 10-month moving average, the investor switches to cash and earns the return on cash in the subsequent month. The trend-following filter thus switches the investor between equities and cash

depending on the level of the index relative to its 10-month moving average.

The solid line in Figure 1 represents the real PWR over time, assuming a 20-year decumulation period and perfect foresight. As Figure 1 shows, the real PWR is generally higher than the equivalent series generated by the equity buy-and-hold risk engine (the dotted line), which is an encouraging start. We calculated the distribution of the PWR generated by the trend-following equity risk engine by first calculating the real return achieved in each calendar year of our sample with the trend-following filter. We then repeated the Monte Carlo analysis, this time drawing from the set of real annual returns generated by the trend-following filter.⁶ The solid line in Figure 2 shows the distribution of the PWRs generated by the trend-following investment strategy. There is a substantial shift to the right in the distribution compared with the distribution produced by the buy-and-hold equity strategy (the dotted line in Figure 2), and the PWR distribution is much more concentrated around its median value of about 9%. The final column in Panel A of Table 2 presents the percentiles of this distribution and shows that around 90% of the time, the PWRs produced by the trend-following risk engine are greater than those produced by the equivalent buy-and-hold equity strategy (shown in the second column in Panel A). In fact, at lower probability levels, the PWRs are nearly double those for the 100% buy-and-hold equity strategy.

The final column in Panel B of Table 2 provides summary statistics of the annual real returns generated by the trend-following strategy and offers a clue about the superior PWRs achieved by using the trend-following strategy. The average real return of 8.84% produced by the trend-following strategy compares very favorably with the 6.82% produced by the buy-and-hold strategy. Perhaps even more important, however, are the one-third reduction in annual volatility, from 14.29% to 9.86%, and the halving of maximum drawdown, from 76.8% to 34.88%. In keeping with the findings of previous research in this area, the trend-following filter applied here reduces both volatility and maximum loss, which leads to a reduction in sequence risk, allowing for noticeably higher PWRs in virtually all cases except those greater than the 90th percentile.

But What about Transaction Costs?

In achieving lower sequence risk, the trend-following filter requires that the investment be switched

between the risky asset class—in this case, the S&P 500—and cash. Before dealing with the difficult issue of historical transaction costs, however, we must first address holding costs. The trend-following literature already discussed has found, for a wide range of asset classes and historical investment periods, that the trend-following filter described here tends to require investment in the risky asset class about two-thirds of the time. Indeed, this is also our finding for the S&P 500 over 1872–2014. If we assume that a cash balance attracts a much lower holding fee than an investment in equities, then in the long term, investors in a trend-following portfolio should expect to pay only two-thirds of the holding costs (management fees) that they would otherwise pay in a buy-and-hold strategy for the same risky asset.

A transaction charge would be payable only in the event of a switch. Ap Gwilym et al. (2010) applied the trend-following filter used here to the MSCI World Index (in dollars) over 1971–2008 and found seven switches (round-trip trades) per decade. We found that the number of switches for the S&P 500 over the nearly 150-year period we analyzed was slightly less than seven per decade. Regarding switching costs, Hurst et al. (2014) investigated the benefits of trend following by applying the sort of trend-following filter used in this article to a century of US capital market data. The authors found that the filter enhanced risk-adjusted returns considerably over the last century or so. In arriving at these results, Hurst et al. estimated (and used) one-way transaction costs as a proportion of the investment's value in developed-economy equities: 0.36%, 0.12%, and 0.06% for 1903–1992, 1993–2002, and 2003–2012, respectively. Finally, in their investigation of trend following for a range of asset classes, using 1994–2015 data, Clare et al. (2016) based equity transaction costs on exchange-traded fund fees, using one-way transaction costs of 0.20% of the investment's value, and found that the trend-following filters still outperform buy-and-hold comparable investments by an impressive margin. For example, they found that applying the same simple 10-month moving-average signal used in this article to developed-economy equities produced an annualized return of 8.0%, a Sharpe ratio of 0.79, and a maximum drawdown of 11.6%. The equivalent buy-and-hold portfolio produced an annualized return of 6.6%, a Sharpe ratio of 0.33, and a maximum drawdown of 46.6%.

To add further insight into the possible effects of transaction costs, we can calculate a breakeven

switching fee, which we define as the one-way transaction cost that equates the returns on a trend-following strategy applied to the S&P 500 with those produced by a buy-and-hold investment in the S&P 500, over the full sample period. This breakeven value turns out to be 1.35%. To put this calculation into perspective, Hurst et al. (2014) suggested that a one-way transaction cost of 0.36% should be used for US equities over 1903–1992, whereas Jones (2002) estimated that one-way transaction costs for US stocks over 1900–2001 average 0.38%. We can recalculate the 20-year PWRs generated by the trend-following strategy applied to the S&P 500. When we set the one-way transaction cost to Hurst et al.'s recommendation of 0.36%, we obtain an average PWR of 9.68%, compared with the S&P 500 buy-and-hold approach, which produces a PWR of 8.8%. Finally, because no investors will be implementing such a strategy *in the past*, it is probably pertinent to consider Hurst et al.'s estimate of 0.06%, based on the authors' practical experience, as the one-way transaction cost for trading US equities over 2003–2012.

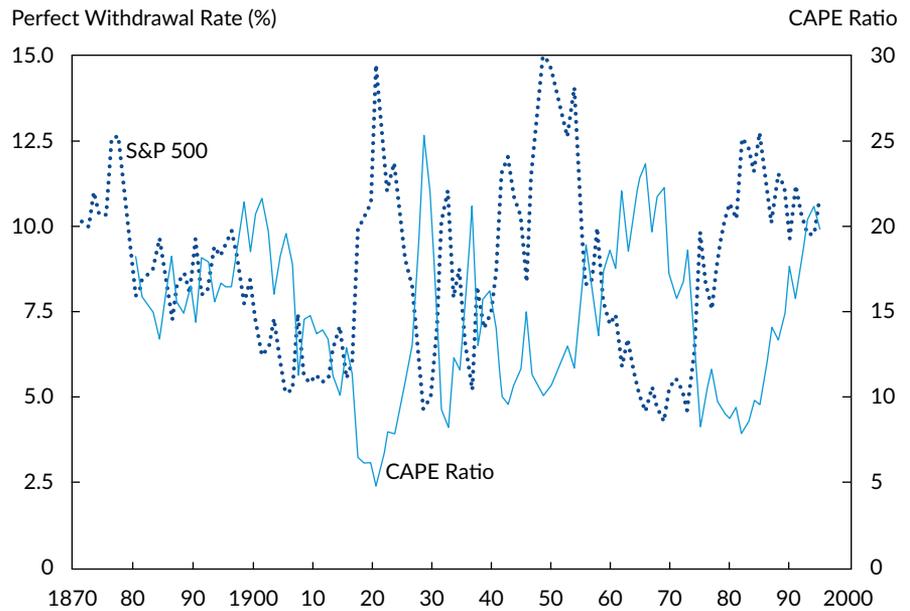
So, the holding costs of trend-following strategies are generally two-thirds of the holding costs of a buy-and-hold equivalent. In addition, switches are relatively rare, at least when trend following is applied at the lower, monthly frequency, and are unlikely to have occurred often enough in the past to eliminate the benefits of the trend-following approach.

Can Equity Valuation Measures Help in Securing Higher Withdrawals?

In this section, we discuss the relationship between the CAPE ratio and PWRs; in particular, we try to determine whether knowledge of the CAPE ratio can help investors achieve higher withdrawal rates.

The Relationship between the CAPE Ratio and PWRs. If a simple trend-following investment strategy facilitates superior withdrawal rates most of the time, it is natural to ask whether other market-timing or valuation indicators can help identify withdrawal amounts that provide similarly “improved” solutions. In particular, such measures as the CAPE ratio (Shiller 2001) have been shown to have some predictive power for longer-run equity returns.⁷ **Figure 3** shows the time-series plot of beginning-period CAPE ratios against the 20-year real PWR

Figure 3. Real PWR for 20-Year Decumulation with 100% US Stock Investment: S&P 500 and CAPE Ratio



generated with the buy-and-hold equity strategy. If the earnings yield is high (and thus the CAPE ratio is low), above-average equity returns are indicated and we would expect a higher perfect-foresight PWR for the subsequent 20-year period. Figure 3 illustrates this dynamic clearly, with the CAPE ratio's low points in 1920, 1930, and 1980 associated with high subsequent PWRs.

We now consider two very different periods of financial market history⁸—the 20-year period from 1995 and the 20-year period from 1973—(1) to examine in more detail the potential benefits of updating withdrawal rates annually using our Monte Carlo method, (2) to assess the benefits of trend following in this adaptive PWR framework, and (3) to investigate the possibility of integrating the “predictive” qualities of the CAPE ratio, also updated annually.

1995–2015. Table 3 (available online at www.cfapubs.org/doi/suppl/10.2469/faj.v73.n4.5) presents the results of using the buy-and-hold equity portfolio as the risk engine for the 20-year period beginning in 1995. The second column in the table shows that real equity returns for the first five years of the sample were very high, suggesting the likelihood of low sequence risk (which is indeed the case). The perfect-foresight, real PWR is 10.781%, giving a real PWA of \$10,781 a year for each of the 20 years.

In the columns headed “Monte Carlo Median PWA” in Table 3, for each year in our sample we report

new, median PWAs generated by applying the Monte Carlo process. More precisely, we began by generating the PWR using the Monte Carlo process and 20,000 annual real return draws. We then calculated the median of the generated distribution to give the PWA in the first year (\$8,545). At the end of the first year, we repeated this exercise, with the investment horizon now at 19 rather than 20 years. We drew a series of 19 annual real returns 20,000 times to create a new distribution and median PWA—and so on. The median PWA changes each year, depending on the value of the investment pot at the end of the previous year.⁹ Using this process, we can see in Table 3 that after the initial 5 years of good investment performance, the investment pot reaches more than \$188,000 with 15 years to go, allowing for a withdrawal amount of \$19,654. Things take a turn for the worse in 2008, when a 39% fall in the S&P 500 leads to a fall in the PWA from \$10,629 to just under \$6,000 for 2009.

The final set of results, presented in the columns headed “CAPE-Based PWA,” is generated by using the fitted value of the PWR based on the CAPE ratio at the beginning of each year and the simple linear regression just described, updated annually to the end of each prior year. The inverted CAPE values appear in the third column of the table (headed “EY Start”; EY is the inverted CAPE ratio). The fairly low withdrawal rates in the early years, together with robust investment returns, lead to wealth reaching more than \$216,000 by the end of 1999. Together with

the CAPE-driven PWRs, this increase leads to higher withdrawal amounts in the final years than those suggested by the Monte Carlo method. For example, the final withdrawal without the CAPE information would be \$8,715, compared with \$14,037 with it. It appears, then, that knowing the value of the CAPE ratio at the start of the year could lead to a superior withdrawal experience for investors.

In **Table 4** (available online at www.cfapubs.org/doi/suppl/10.2469/faj.v73.n4.5), we repeat all the calculations reported in Table 3 but with the trend-adjusted S&P 500 real returns as the risk engine. First, note that the perfect-foresight PWR of 12.31% is higher than the 10.78% in Table 3. So, using trend-following-filtered returns leads to a higher PWR, as we have seen previously. Note also how the real returns generated by the trend-adjusted strategy (second column of Table 4) lead to a real return of -4.4% in 2002 compared with -22% generated by the buy-and-hold strategy (second column of Table 3), whereas a real return of 1.3% in 2008 compares favorably with -39% generated by the buy-and-hold strategy in the same year. The higher real returns in these two years, in particular, facilitate higher PWAs. For example, the withdrawal in 2014 is \$10,991 using the trend-following approach, compared with \$8,715 using the buy-and-hold risk engine. However, an even higher withdrawal rate is achieved when we combine trend-following returns with information from the CAPE ratio. For example, the last three withdrawals are \$12,847, \$13,188, and \$15,868, which compare quite favorably with the Monte Carlo results produced by the unadjusted raw equity returns in Table 3: \$6,941, \$7,410, and \$8,715, respectively.

It thus appears that the trend-following approach, when combined with the predictive power of the CAPE ratio, has the potential to produce a much better retirement experience during a period when raw investment returns are high in the early years.

1973–1993. What happens if we repeat this exercise for a period of financial history characterized by poor returns in the early years—for example, the 20 years beginning in 1973?

The second column in **Table 5** (available online at www.cfapubs.org/doi/suppl/10.2469/faj.v73.n4.5) shows real US equity returns for each year from 1973 to 1992. In 1973 and 1974, real returns were around -24% and -34%, respectively, suggesting the possibility of high sequence risk for anyone starting the decumulation journey in 1973. Although returns recovered later in the period, the damage was done:

The perfect-foresight PWR was only 4.59% for the 20-year period (a PWA of \$4,591 from a starting pot of \$100,000), emphasizing that birth date can have a major bearing on one's income in retirement. Both the Monte Carlo median metric and the CAPE valuation metrics produce substantially reduced PWAs relative to those reported in Table 3. For example, Table 3 shows that the Monte Carlo median approach gives a final withdrawal amount of \$8,715, whereas the CAPE-based approach yields a final withdrawal value of \$14,037; the equivalent values for 1973–1992, shown in Table 5, are \$5,664 and \$4,812, respectively.

But what if we repeat this exercise using trend-adjusted equity returns over the same period? **Table 6** (available online at www.cfapubs.org/doi/suppl/10.2469/faj.v73.n4.5) reports the results. First, note the absence of really severe negative returns in the second column, which allows the perfect-foresight PWR to rise by a third, to 6.148% a year. Similarly, the Monte Carlo and CAPE-based results suggest that much higher withdrawals are possible, particularly in the early years, relative to the trend-unadjusted returns reported in Table 5. However, Table 6 shows that the CAPE-based annual withdrawals are not as high as those produced by the Monte Carlo approach. In this case, trend following alone produces the best withdrawal results.

Conclusion

In this article, we have drawn attention to a number of key features of the much-neglected investment aspects of retirement planning and execution. We have also seen how differences in birth dates can dramatically affect retirement income. Although financial planning professionals may recognize the reduction of sequence risk as an important aspect of the decumulation journey, relatively little awareness of sequence risk exists in the mainstream asset management and investing strategy literature, possibly because there is no widely accepted measure of this risk in practice. The challenge of creating investing strategies for the decumulation phase, beyond the risk-free TIPS (Treasury Inflation-Protected Securities) portfolios of, say, Sexauer et al. (2012), has barely begun. The choice seems to be between controlling tail risk with derivatives (Milevsky and Posner 2014) and portfolio-timing adjustments into and out of cash (Strub 2013). Our study is firmly in the latter camp. We have shown that using a simple trend-following strategy results in significantly reduced sequence risk while generating a robust level of average returns and thus an enhanced,

feasible withdrawal rate. We have also shown that there is potentially useful information in market valuation measures, such as the CAPE ratio, which could help inform withdrawal rates when these measures are adapted on a regular—possibly annual—basis.

Our analysis represents an attempt to identify a risk engine that can bring investors closer to their own perfect withdrawal rate. We acknowledge, however, that there may well be superior alternative investment strategies out there. Certainly, a process that encompasses multiple asset classes, rather than the equity-only approach we investigated, may provide

an even better defense against the pernicious effects of sequence risk. We believe that the research focus should shift to the identification of suitable risk engines for decumulation journeys. Others have already designed a fine chassis, but a chassis without an engine will simply rust in the backyard.

Editor's Note

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Notes

1. See www.econ.yale.edu/~shiller/data.htm.
2. There is a tendency in the finance industry to use the terms *momentum* and *trend following* almost interchangeably, and yet they are subtly different. Trend following is closely related to momentum investing, which was originally identified by Jegadeesh and Titman (1993), but is fundamentally different in that it does not order the past performance of the assets of interest, though it does rely on a continuation of, or persistence in, price behavior based on some technical rule. Moskowitz, Ooi, and Pedersen (2012) referred to the trend-following filter that we use here as “time series momentum” and referred to the Jegadeesh–Titman momentum effects as “cross-sectional momentum.”
3. For evidence of how trend-following filters can be used to enhance asset allocation, predominantly by reducing maximum drawdowns on portfolios, see Clare, Seaton, Smith, and Thomas (2016).
4. Clare et al. (2013) also showed that the 10-month calculation period for the average is not critical to their results. They found that 6-, 8-, 10-, and 12-month calculation rules produce very similar results. Examining the usefulness of the same trend-following rule for a range of asset classes, Clare et al. (2016) also found that the results are not sensitive to the choice of moving-average calculation.
5. In order for trend-following filters such as the one described in this article to produce attractive, risk-adjusted returns by reducing maximum drawdowns, broad markets need to “trend” over periods greater than the frequency of the rule’s application. The findings of Faber (2007); ap Gwilym, Clare, Seaton, and Thomas (2010); Hurst, Ooi, and Pedersen (2014); Clare et al. (2016); and others—using a range of asset classes and sample periods—suggest that financial markets do tend to trend. The trending in markets is, in turn, probably related to behavioral drivers, such as herding and overconfidence. If these ideas hold true, then so long as these biases exist, markets will tend to trend and trend following will continue to produce attractive risk-adjusted returns. But the question of why trend following works is beyond the scope of this study. We use it here to demonstrate that it is possible to implement a strategy that can bring investors closer to their PWR. Other researchers or investors may know of, or prefer, other investment strategies.
6. An alternative to the Monte Carlo approach described here is to analyze the 1,500 unique 20-year periods. Following the suggestion of an anonymous referee, we analyzed these 1,500 series. We found that the average PWR for the buy-and-hold and trend-following strategies was 8.8% and 9.6%, respectively, a difference that we found to be statistically significant at the 99% confidence level, using standard errors robust to moving-average errors. These results, the empirical distribution, and the data are available from the authors upon request.
7. Blanchett et al. (2012) introduced both bond yields and the CAPE ratio as indicators of market valuation.
8. A common feature of the financial planning literature is the analysis of different periods of financial history to explore sustainable withdrawal rates in very different environments (see, e.g., Chatterjee, Palmer, and Goetz 2011).
9. We believe this to be a simpler approach to creating adaptive PWAs than the adaptive rules found in prior literature—see, for example, Pye (2000); Guyton (2004); Stout and Mitchell (2006); Robinson (2007); Blanchett and Frank (2009); Bernard (2011); Mitchell (2011).

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