Assessing Tactical Investment Strategies Using Short Histories

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Introduction and Summary

The primary investment risks are *volatility*, the day-to-day changes in portfolio value; the risk pf large price *drawdowns* during market corrections and the *longevity risk* of running out of money before death.

Volatility is characterized by the standard deviation of price returns. Drawdown risk is characterized by the maximum observed drawdown. Longevity risk is assessed using historical simulation.

Historical simulation was developed independently by Larry Bierwirth[1], William Bengen[2] and Moshe Milevsky, *et al.*[3] in 1994. The author independently developed similar capabilities[4]. We reasoned that the historical probability of exhausting a portfolio within a given time horizon could be determined using historical returns or return sequences.

Bengen's work is the best known to financial planners and many key financial planning conclusions can be found in his book[5].

Part 1 illustrates three ways to implement historical simulation using portfolios with fixed allocations to large cap US stocks and intermediate term bonds.

A limitation of *sequential* historical simulation is that long histories are required. Part 2 shows how the price history can be effectively enlarged by drawing at random from the existing returns or by approximating the existing returns as a distribution.

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[1] Investing for Retirement: Using the Past to Model the Future by Larry Bierwirth, *Journal of Financial Planning*, January 1994.

[2] Determining Withdrawal Rates Using Historical Data by William P. Bengen, *Journal of Financial Planning* , October 1994.

[3] Asset Allocation, Life Expectancy and Shortfall by Kwok Ho, Moshe Arye Milevsky and Chris Robinson, *Financial Services Review* (3), 1994 and Asset Allocation Via the Conditional First Exit Time or How to Avoid Outliving Your Money by Moshe Arye Milevsky, Kwok Ho, and Chris Robinson, *Review of Quantitative Finance and Accounting*, (9) 1997.

[4] Sustainable Withdrawal Rates and How Alternative Strategies Affect the Heirs by Peter James Lingane, 2007 Personal Financial Planning Conference, California CPA Education Foundation.

[5] *Conserving Client Portfolios During Retirement*, William P. Bengen FPA Press, 2006.

The analytical solution[6] and the free Monte Carlo simulator[7] for longevity risk both require a return distribution.

Part 3 shows how mortality weighting is sued to estimate the value of the portfolio at death.

Historical simulation has been commonly used to design sustainable withdrawal rates from retirement and endowment portfolios. This article argues that portfolio longevity is an important characteristic of an investment strategy. A strategy which reduces volatility and drawdown is lower risk only if it also increases longevity. This is discussed in Part 4.

Part 5 and Appendix C illustrates how volatility, drawdown and longevity risks can be used to rank a variety of investment strategies. Tactical strategies are identified which, historically, have had substantially better drawdown and longevity characteristics than the traditional 60:40 strategy while exhibiting similar moderate volatilities.

The simulations discussed in this article employ inflation-adjusted returns because

- This avoids the need to model correlations among portfolio securities and with inflation.
- Using inflation-adjusted returns simplifies some calculations. For example, periodic withdrawals and terminal values are automatically inflation-adjusted.
- The Central limit theorem teaches that combinations of random variables tend toward normal or lognormal distributions. Inflation-adjusted portfolio returns are more normal-like than the returns of individual portfolio elements.

[6] Equation 9.4 in *The Calculus of Retirement Income,* Moshe A. Milevsky, Cambridge University Press, 2006. See also, A Gentle Introduction to the Calculus of Retirement Income: What is Your Retirement Risk Quotient? by Moshe A. Milevsky, June 1, 2007, www. yorku.ca/Milevsky/Papers.html.

[7] www.portfoliovisualizer.com.

Part 1. Application to Long Histories

Methodology.

The monthly inflation-adjusted returns of portfolios with fixed allocations to stocks and bonds were synthesized by combining the historical returns for large cap US stocks and for intermediate term government bonds and adjusting for historical inflation using the following formula[8]. EA is the equity allocation.

(EA * (1 + LrgCapUS) + (1 – EA) * (1 + IGBond)) / (1 + Inflation) – 1

Example, the monthly returns for US Stocks, IGBond and Inflation were negative 5.02%, negative 0.53% and positive 0.30% for January 2000. The inflation adjusted return for a 60% equity portfolio was negative 3.51346%.

Inflation adjusted portfolio returns offer several advantages.

- It is not necessary to model the correlation between historical returns and historical inflation.
- The returns are more normal-like, courtesy of the Central Limit Theorem.
- Withdrawal rates and portfolio values are automatically inflation-adjusted.

The monthly offtake ls the annual withdrawal rate times the initial portfolio value divided by twelve. Withdrawals are taken at month-end.

The failure rate is the frequency with which the portfolio is exhausted before the end of the simulation interval. The failure rate is measured as the ratio of the number of failed simulations to the total number of simulations.

The sustainable withdrawal rate (SWR) is as the annual withdrawal rate which produces a 5% failure rate over the simulation interval.

The tables show the median inflation-adjusted terminal values and the median mortality weighted inflation-adjusted terminal values. Mortality weighting is described in Part 3. Mortalities are for a 65-year-old male.

Simulations use one of four techniques.

- **Sequential Historical**. The first simulation typically starts at the end of December 1925 and applies the historical monthly returns, in sequence, to the next 360 months. The second simulation starts at the end of January 1926 and applies the historical returns to the subsequent 360 months. The final simulation, number 780 in this example, starts at the end of December 1990 and concludes at the end of December 2020.

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[8] Historical monthly returns are generally from *Stocks, Bonds, Bills and Inflation*, Ibbotson Associates, annually since 1983. Annual updates are currently published by Duff and Phelps.

Data for LrgCapUS and IGBond after 2018 are from curated data/xlsx at www.lingane.com/qi. Inflation data after 2018 are CPI-U (all cities, all items, not seasonally adjusted) from the US Department of Labor.

Different starting and ending dates can be used so long as each simulation is at least as long as the time interval of interest and so long as there are sufficient simulations (starting dates) in the historical record to estimate the failure rate with adequate precision.

- **Random Historical**. Each simulation draws the monthly returns, at random with replacement, from the history.

  Each offtake rate was simulated using the same sequence of historical returns by resetting the random seed to the same value after each change in the offtake rate.

- **Random Historical Without Replacement**. Simulations are as Random Historical except that a return, once picked, is excluded from the return pool until all returns have been utilized.

- **Distribution**. Each simulation draws monthly returns, at random with replacement, from the normal or lognormal distribution appropriate for the portfolio.

  The parameters of the normal or lognormal distribution are the arithmetic monthly mean and standard deviation of the historical returns specific to that portfolio. For example, when simulating a 60:40 portfolio using a normal distribution, the monthly mean and standard deviation of the normal distribution are 0.0512 and 0.0334 (Table 1).

  When annual means and standard deviations were required, standard deviations were annualized using the Levy-Gunthorpe formula[9]

$$s_a^2 = [s_m^2 + (1+m_m)^2]^{12} - (1+m_m)^{24}$$

  where s_a and s_m are the annual and monthly standard deviations and m_m is the monthly arithmetic mean. The annualized mean is $(1 + m_m)$^12 – 1.

  Empirical return distributions for three binary portfolios are shown in Figure 1 and compared to normal and lognormal distributions with monthly parameters determined as described above. The normal and lognormal distributions are nearly identical because the standard deviations are small.

  I do not claim that the distributions are normal. The issue is whether the distributions are normal enough to provide useful estimates of sustainable withdrawal rates.

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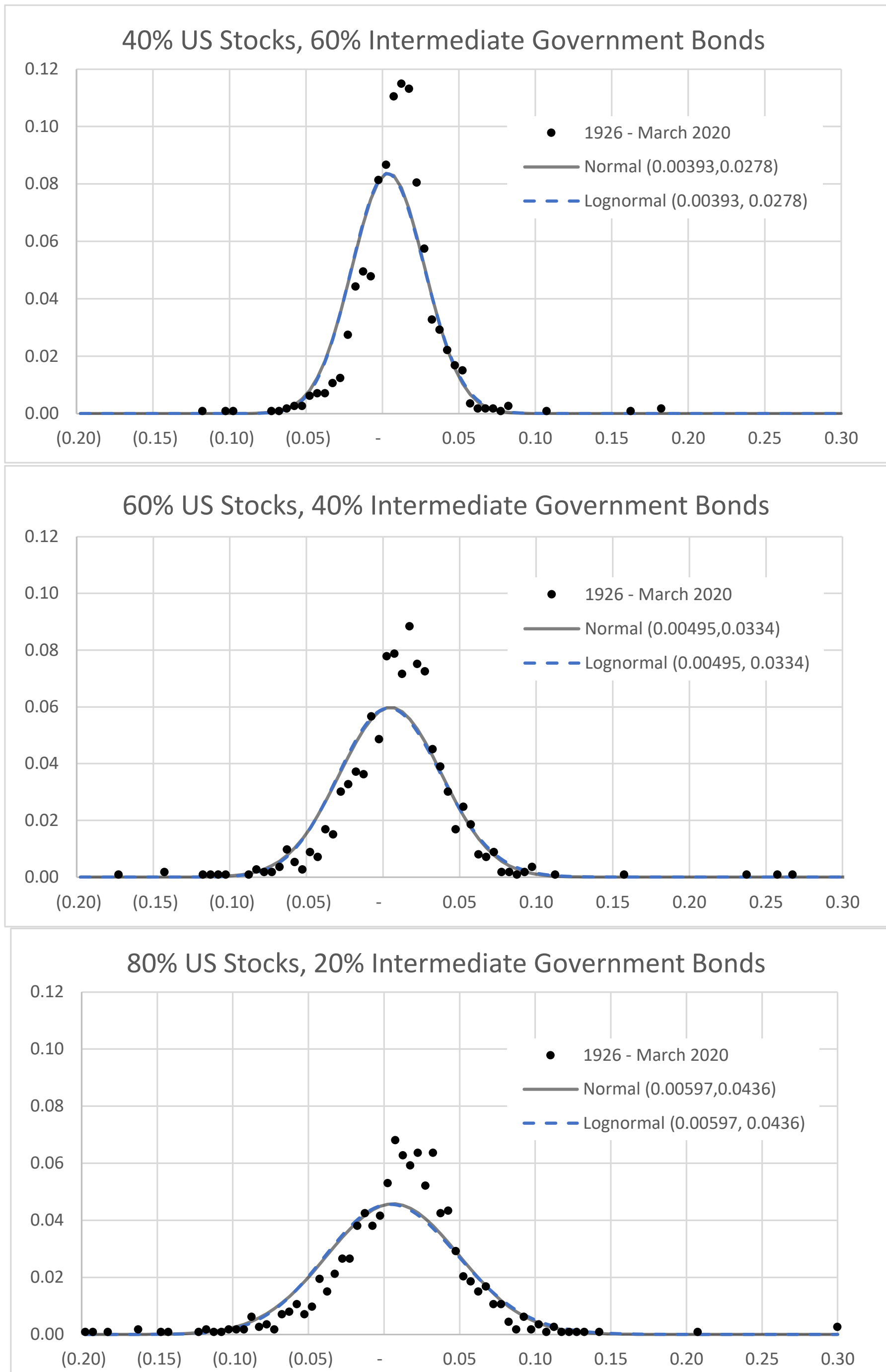
[9] Haim Levy and Deborah Gunthorpe, "Optimal Investment Proportions in Senior Securities and Equities Under Alternative Holding Periods," *Journal of Portfolio Management*, Summer 1993. Cited by the *SBBI Yearbook.*

For the derivation and discussion, see "What's Wrong with Multiplying by the Square Root of Twelve," by Paul D. Kaplan, Morningstar Inc, January 2013.

The distributions overestimate the frequency of negative returns, which probably explains the slightly smaller sustainable withdrawal rates for the normal distribution technique in Table 1.

Figure 1. Historical Inflation-Adjusted Monthly Returns Compared to Normal and Lognormal Distributions. 1926 – March 2020.



Source: HistoricalReturns.xlsx

Table 1. Sustainable Withdrawal Rate (SWR) as a Function of the Equity Allocation and Simulation Technique. Portfolios contain LrgCapUS and IGBond with the equity allocation shown. There are 780 simulations, each 360 months long, with starting dates from 1926 through 1991. The calculations are performed in C# using HistoricalSimulation.sln and the random seed is 4. The initial portfolio value is $1000.

Equity Allocation	Sequential Historical SWR, %	Random Historical SWR, %	Normal SWR, %	Sequential Historical Terminal Value, $	Sequential Historical Weighted Sum, $	Random Historical Terminal Value, $	Random Historical Weighted Sum, $	Normal Terminal Value, $	Normal Weighted Sum, $	Monthly Mean Return	Monthly Std Dev
10%	3.13	3.96	3.89	510	660	430	670	480	690	0.00242	0.0138
20%	3.56	4.13	4.09	470	700	590	750	610	760	0.00296	0.0160
30%	4.01	4.18	4.11	470	730	850	880	860	900	0.00350	0.0195
40%	4.21	4.20	4.09	670	800	1,180	1,030	1,290	1,090	0.00404	0.0238
50%	4.26	4.18	3.92	1,000	1,000	1,580	1,200	1,760	1,280	0.00458	0.0285
60%	4.26	4.08	3.99	1,400	1,200	2,100	1,400	2,100	1,470	0.00512	0.0334
70%	4.26	3.95	3.71	1,900	1,560	2,600	1,660	2,530	1,640	0.00566	0.0385
80%	4.23	3.80	3.64	2,550	1,780	3,180	1,930	3,253	1,980	0.00620	0.0436
90%	4.16	3.65	3.42	3,300	2,100	3,700	2,200	3,380	2,150	0.00674	0.0489
100%	4.08	3.41	3.45	4,000	2,400	4,400	2,500	4,250	2,340	0.00728	0.0542

Source: HistoricalSimulations_01152021.xlsx.

The first observation from Table 1 is that the equity allocation has only a small effect on the sustainable withdrawal rate over a broad range of equity allocations[10].

As illustrated in Appendix C, buy and hold strategies with low equity allocations have been, historically, the least volatile with the lowest drawdowns and highest Sharpe ratios and UPI values. On the other hand, low equity allocations are associated with a decreased longevity and high equity portfolios have the potential for larger terminal valuations.

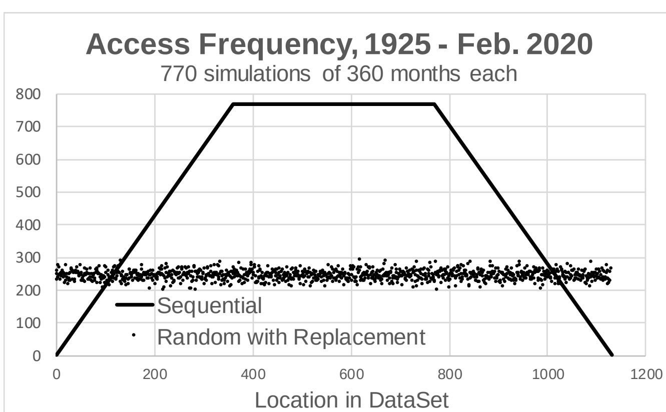
If a buy and hold investor's primary concern is for their own financial well-being, they should consider a portfolio with a lower equity allocation. If the investor has legacy ambitions, if he or she wants to make their children rich or to favor a favorite charity, they may prefer higher equity allocations.

The primary purpose of this article is that the tactical investor need not be concerned about trading their own financial security for a lower volatility. We will see that some tactical strategies provide moderate volatilities with a low risk of running out of money before death

The distinction between investors with and without legacy ambitions creates a dilemma when recommending a strategy. The strategies highlighted in Part 5 are suitable for investors whose primary concern is their personal financial security. Investors with legacy ambitions may prefer more volatile strategies which tend to have higher bequest potential.

Uniform sampling is a challenge for the sequential historical technique. As is shown as the solid line in Figure 2, the first and last returns are sampled once, the second and next to last returns are sampled twice and returns between 361 and 771 are sampled 770 times each. (There are 770 rather than 780 months in the time interval tested.)

Figure 2. 1130 monthly returns between January 1926 and February 2020 sampled sequentially by 770 simulations of 360 returns each.

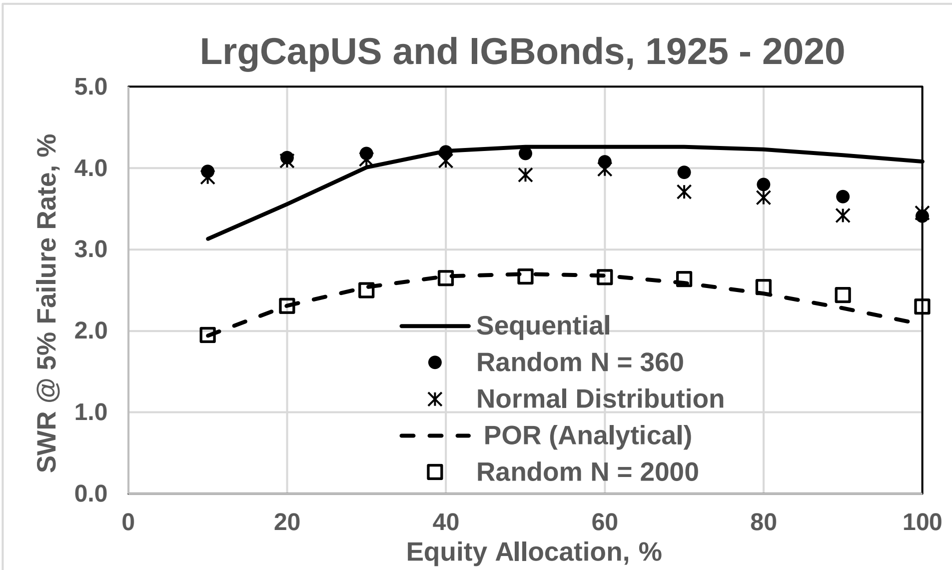


[10] This effect was first observed by Bengen; see his Figure 2A.

Random sampling with replacement accesses the returns more uniformly.

The second observation from Table 1 is that the three techniques provide similar sustainable withdrawal rates. This is also illustrated in Figure 3.

Figure 3. Sustainable Withdrawal Rate as a Function of Equity Allocation, Simulation Technique and Length of Simulation Interval.



Source: HistoricalSimulations 01152021.xlsx

The similar results with sequential and random simulations suggests that neither serial correlation[11] nor normality nor nonuniform sampling has a dominant influence when estimating sustainable withdrawal rates from historical returns.

If the simulation interval is lengthened from 360 months, the number of failures increases and the sustainable withdrawal rate decreases. In the limit, the sustainable withdrawal rate is as is shown by the open squares in Figure 4.

The dashed line is the sustainable withdrawal rate from the analytical expression developed by Milevsky assuming a lognormal return distribution[12] and an infinite time horizon.

The result is a formula for the risk of failure before death, what Milevsky calls the probability of ruin (POR), as a function of the mean and standard deviation of the inflation-adjusted returns.

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[11] The serial correlations for the 1130 inflation-adjusted returns are 0.09, 0.08 and 0.08 for the 40%, 60% and 80% equity portfolios.

[12] Equation 9.4 in "The Calculus of Retirement Income" by Moshe A. Milevsky, Cambridge University Press, 2006. This formula also includes the effect of mortality, in an approximate fashion. The mortality feature has been disabled since mortality weighted sustainably withdrawal rates are not appropriate for individuals – though they are of high interest to pension funds and insurance companies.

Milevsky recommends the following syntax in EXCEL.

GAMMADIST(annual withdrawal rate, alpha, beta, TRUE)

alpha = $(2 \mu + 4 \lambda) / (\sigma^2 + \lambda) - 1$

beta = $(\sigma^2 + \lambda) / 2$

$\lambda = 0$, which disables mortality considerations.

μ and σ are annualized mean and annualized standard deviation of the portfolio returns, determined as described previously.

Milevsky's formula was developed for long time horizons, such as would be appropriate for a pension fund or young child. The formula overstates failure rates over a shorter interval.

Monte Carlo simulation for a buy and hold strategy of 60% large capitalization US stocks and 40% intermediate term US Treasure bonds indicates that a 4.08% initial withdrawal rate would produce a 5% failure rate over thirty years. (Subsequent withdrawals are adjusted for inflation and are unaffected by the growth or shrinkage of the portfolio.) Milevsky's formula indicates that a 4.08% initial withdrawal rate would produce a 25% failure rate over an infinite time horizon. Distribution parameters are for the 1926-2020 interval.

Table 2. Sustainable Withdrawal Rate as a Function of Equity Allocation and the Length of the Simulation Interval. Portfolios contain LrgCapUS and IGBond with the equity allocation shown. The mean inflation-adjusted returns and the standard deviations are for the interval 1926 – 2020.

Equity Allocation	Random Historical n = 240	Random Historical n = 360	Random Historical n = 480	Random Historical n = 1000	Random Historical n = 2000	Milevsky Eqn. 9.4 n = ∞	Monthly Mean	Monthly Std Dev	Annualized Mean	Annualized Std Dev
10%	5.42	3.96	3.20	2.29	1.95	1.94	0.00242	0.0138	0.0294	0.0491
20%	5.56	4.13	3.42	2.58	2.31	2.31	0.00296	0.0160	0.0361	0.0573
30%	5.54	4.18	3.55	2.76	2.50	2.54	0.00350	0.0195	0.0428	0.0703
40%	5.47	4.20	3.57	2.85	2.65	2.67	0.00404	0.0238	0.0496	0.0863
50%	5.33	4.18	3.52	2.88	2.67	2.70	0.00458	0.0285	0.0564	0.1040
60%	5.20	4.08	3.44	2.85	2.66	2.68	0.00512	0.0334	0.0632	0.1228
70%	5.04	3.95	3.35	2.79	2.64	2.59	0.00566	0.0385	0.0701	0.1425
80%	4.86	3.80	3.22	2.70	2.54	2.46	0.00620	0.0436	0.0770	0.1625
90%	4.63	3.65	3.05	2.58	2.44	2.28	0.00674	0.0489	0.0839	0.1836
100%	4.42	3.41	2.83	2.42	2.30	2.08	0.00728	0.0542	0.0909	0.2050

Part 2. Application to Short Histories

Few historical datasets have as much history as the 96-year SBBI dataset. It is often necessary, therefore, to use shorter histories when estimating the effects of portfolio compositions.

The most important challenge facing the use of short histories is judging whether the market conditions in the short interval are representative of the future. The second challenge is that short histories reduce the precision with which the SWR is determined and render Historical Simulation impractical.

Table 1 and Figure 3 suggest that random simulations may be able to estimate sustainable withdrawal rates when sequential simulation is not practical.

Table 3. Small SBBI Datasets, 60% Equity Allocation. The Initial portfolio value is $1000. There are 780 simulations of 360 months each. Median terminal values are inflation-adjusted but are not mortality weighted.

The historical intervals and the mean and standard deviation of the Normal distributions of inflation-adjusted monthly returns from within these intervals are as indicated.

The first entry corresponds to a seed of 4 and the second to a seed of 27 for Random Historical and Random w/o Replacement Historical and to different realizations of the Normal distribution for Random Normal simulations.

Historical Interval	Random Historical SWR, %	Random w/o Replacement Historical SWR, %	Random Normal SWR, %	Random Historical Terminal Value, $	Normal Terminal Value, $	Mean, Monthly Returns	Std Dev, Monthly Returns
1926 - 2020	3.96 3.96	4.25 4.17	3.76 3.98	1,984 2,011	2,088 1,930	0.00512	0.0334
1972 - 2020	4.18 4.25	4.57 4.67	4.25	1,474 1,559		0.00482	0.0278
1986 - 2020	4.79 4.99	5.49 5.43		2,000 2,026		0.00549	0.0261
1926 - 1945	3.60 3.46	4.93 4.85	3.36 3.32	3,584 4,202	3,616 3,535	0.00676	0.0517
1946 - 1965	5.08 5.18	5.77 5.90	5.12 5.18	1,900 1,777	1,842 1,851	0.00534	0.0229
1966 - 1985	2.81 2.62	3.45 3.44	2.74 2.44	713 765	680 860	0.00222	0.0295
1986 – 2005	5.22 5.00	6.32 6.29	5.24 5.18	2,597 2,951	2,711 2,690	0.00621	0.0278
2000 – 2020 21 years	3.77 3.71	4.00 4.41	3.60 3.50	1,080 1,082	673 672	0.00359	0.0253

Source: Random Sequential.xlsx and EF Performance.xlsx

To test this hypothesis, the SBBI data were divided into five subintervals of approximately 240 months each. Results are in Table 3.

The sustainable withdrawal rates determined by the Random Historical and Normal techniques are similar, as are the terminal values.

Sustainable withdrawal rates determined by the Random Historical without Replacement technique are larger than the other SWR values. Since Random Historical without Replacement technique provides more optimistic results than with Replacement and since with Replacement provides similar results to the reference Sequential technique, I conclude that not replacing the returns after each draw biases the results in an optimistic direction.

The simulations different seeds provide suggest that the uncertainty in the SWR values is on the order of 0.1%.

The simulation techniques agree that the sustainable withdrawal rate has been different in different time intervals.

All Table Values Should Be Confirmed.

Part 3. Mortality Weighting

The chance of survival from age N to age N + 1 equals the number of living individuals in the population at age N + 1 divided by the number of living individuals in the population at age N.

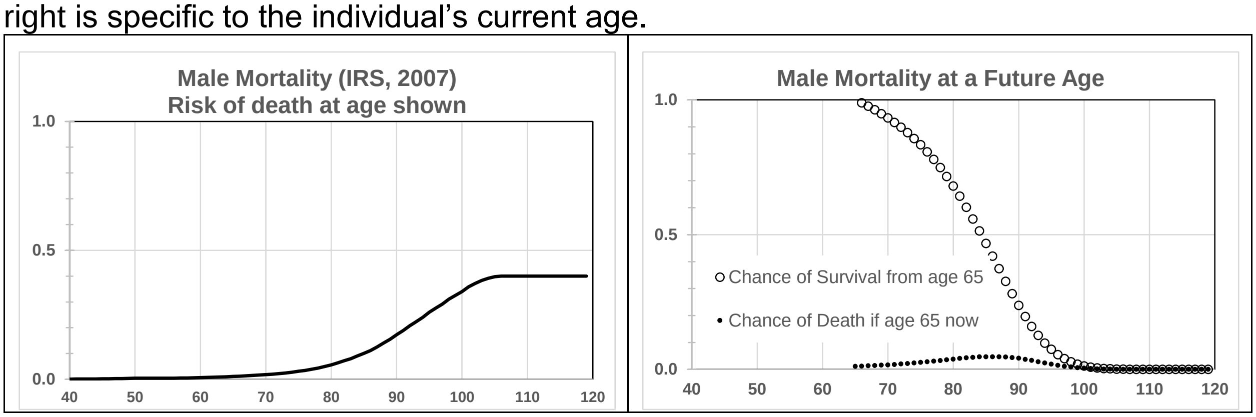
The risk of death at age N is one minus the chance of survival from age N to age N + 1.

The risk of death as a function of age is called a “mortality table.”

There are numerous mortality tables. We are using the IRS “annuitant” table[13] for determining the minimum funding of defined benefit plans.

The risk of death within one year (mortality) is shown on the left side of Figure 5 for a male as a function of his age.

Figure 5. Mortality and Chance of Future Death. The constant mortality after age 105 in the chart on the left reflects a lack of data for the very elderly. The chart on the right is specific to the individual’s current age.



Source: Probabilistic Roth_revised May 2000.xlsm

[13] IRS TD 9310, 2007.

Our interest is not the mortality *per se* but how the chance of someone aged N dying n years in the future can be estimated from the mortalities. This is the chance of surviving from age N to age N + n times the risk of death at age N + n.

Since the chance of surviving from age N to N + n is the product of the chances of surviving to each year from N+1 through N + n, the risk that someone age N will die at age N + n equals

$$\{ (1 + M[N]) * (1-M[N + 1]) * \ldots * (1-M[N + n - 1]) \} * M[N + n]$$

where M[N + i] is the mortality at age i.

The chance of survival from age N to N + n and the risk of someone aged N dying at age N + n are shown on the right side of Figure 5 for a sixty-five-year-old male.

The information summarized in Table 5 indicates that.

- A 65-year-old male has a 1% chance of dying before his 66th birthday.
- He has a 93% chance of living to at least age 70 and a 1.7% chance of dying in his 70th year.
- A 65-year-old female has a 35% chance of living to at least age 90 and a 4.4% chance of dying in her 90th year.

Table 5. Chance of Death, Assuming Currently Aged 65.

Age	Mortality, Male	Chance of Survival	Chance of Death	Mortality Weight	Mortality, Female	Chance of Survival	Chance of Death	Mortality Weight
40	0.00090				0.00051			
45	0.00179				0.00079			
50	0.00415				0.00184			
55	0.00451				0.00316			
60	0.00654				0.00578			
65	0.01102	100%	1.1%	0.011	0.00966	100%	1.0%	0.010
70	0.01797	93%	1.7%	0.016	0.01561	94%	1.5%	0.014
75	0.03106	83%	2.8%	0.023	0.02512	86%	2.1%	0.018
80	0.05592	68%	3.8%	0.026	0.04158	73%	3.0%	0.022
85	0.10038	47%	4.7%	0.022	0.07119	56%	4.0%	0.022
90	0.17340	24%	4.1%	0.010	0.12626	35%	4.4%	0.015
95	0.26010	7.4%	1.9%	0.0014	0.18913	15%	2.9%	0.0044
100	0.33976	1.3%	0.4%	0.00005	0.23416	4.7%	1.1%	0.0005

Source: Probabilistic Roth_revised May 2000.xlsm

The expected value at death or “bequest” is the sum of the year-end values weighted by the chance of death.

Historical simulations typically extend for 360 months. The cumulative mortalities shown in Table 5 indicate that a significant portion of the population will die after thirty years. This is especially true for women and those younger than age 65. It is therefore good practice to simulate a minimum of 360 months; 480 months would be better.

It is tempting to observe that the risk of exhausting one’s portfolio before death is the product of the risk of survival and the risk of portfolio failure. Even a 50% risk of exhausting one’s portfolio before thirty years appears tolerable if the chance of living thirty years is small. That is how an insurance company would view things. But an individual cannot accept so rosy a picture and must demand portfolio success to a very advanced age.

Part 4. Portfolio Longevity

The usual use of historical simulation has been the design of sustainable withdrawal rates from retirement and endowment portfolios. A growing use is to define portfolio longevity as a risk-reward characteristic of the investment strategy, much like the Sharpe Ratio and Ulcer Performance Index (UPI).

Maurer has championed this latter use and has expressed the opinion that the portfolio with the highest SWR is best, even if associated with large drawdowns[14].

The Pinkertons are a risk adverse couple who retired at the end of 2007. They panicked during the 2008 bear market, sold near the bottom and locked-in a one third loss by the time that they re-entered the recovering market[15].

The one third loss increased the annual withdrawal rate to about 6% of the (reduced) portfolio value.

The Pinkertons are in their seventies. Mortality estimates described in Part 3 suggest that there is a 5% chance that one of them will live at least 25 years. The risk of running out of money within 25 years is significant for a 6% withdrawal rate.

If the Pinkerton's are to reduce their risk of financial ruin, they need to reduce spending, access the equity in their home, purchase an immediate life annuity and change their investment strategy.

A life annuity guarantees lifetime income and professional management, Payouts are higher than what can be prudently withdrawn from an individual portfolio because the insurance company knows, in an actuarial sense, when payments will cease whereas an individual must plan for a longer period. Unfortunately, there are no refunds in the event of an early death.

Buy and hold investors like the Pinkertons have few options by which to improve investment performance. One suggestion is to reduce volatility by reducing the portfolio's equity allocation[16].

The late James Cloonan, the founder of the American Association of Individual Investors (AAII), emphasizes that an investor's primary focus should be on having enough[17]. Does adding cash and bonds increase the chances that the Pinkertons will have enough during their remaining years? Reducing the equity allocation will reduce volatility but will reducing the equity allocation make this portfolio "safer?"

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[14] Most recently, e-mail January 16, 2021.

[15] "Taming Drawdowns, Improving Risk-Adjusted Returns" by Peter James Lingane, Don Maurer and Alan J. Zmyslowski, 2017. Available at www.lingane.com/qi.

[16] Charles Rotblut, "Allocating to Manage Risk. A Case Study," *AAII Journal*, July 2017.

[17] *Investing at Level3*, James B. Cloonan, AAII, 2016.

Figure 3 suggests that decreasing the equity allocation from 90% originally to 73% in the reconfigured portfolio should not have a large effect on the sustainable withdrawal rate. This means that reducing the equity allocation should not have a large effect on the risk of running out of money.

To illustrate the use of Portfolio Visualizer's free Monte Carlo simulator[18], the historical monthly returns of the present and decreased equity allocation portfolios were simulated as described in Appendix B.

It turns out that decreasing the buy and hold equity allocation slightly worsens the Pinkerton's risk of running out of money. The Monte Carlo risk of exhausting the portfolio within twenty-five years increases from 33 to 34%. POR, which measures the risk of failure over an infinite time horizon increases from 61 to 77%. See Table 7.

The Pinkertons should consider a tactical investment strategy. Tactical strategies differ from buy and hold in that they adjust the portfolio composition periodically in response to current market conditions.

The SIMPLE relative momentum strategy uses the same investments as the Pinkertons but varies the allocations in response to market conditions[19].

The QQQ dilution strategy varies the allocation between QQQ (which tracks the NASDAQ 100 stock index) and intermediate term Treasury bonds to maintain the portfolio volatility at 0.5% per day[20].

Both tactical strategies are less volatile as measured by monthly standard deviation. Both tactical strategies would have sharply reduced losses during the 2008 bear market as measured by Max Drawdown. Both strategies would have reduced the risk of running out of money to single digits.

These strategies are "safer" than the other Pinkerton portfolio because they reduce volatility, drawdown and the risk of running out of money.

A simulated low risk of running out of money is not a guarantee that the strategy will not fail under future market conditions.

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[18] www.portfoliovisualizer.com. The Monte Carlo simulator models historical returns as an inflation-adjusted normal distribution. The author has no financial interest in this free software.

[19] Equal monthly allocation to the two funds with the highest momentum from among US and foreign large cap stocks, US real estate and US intermediate and long bonds. There is no market timing. FundX momentum is the average of the total returns measured over the trailing 1, 3, 6 and 12 months.

This strategy was backtested using curated data for LrgCapUS, USREIT, IGBond and SBBISml and FastTrack data for VUSTX; see www.lingane.com/qi. Implemented on a forward going basis, the strategy would trade among VOO, VEU, VNQ, BND and TLT.

[20]The QQQ Dilution strategy consists of single exchange-traded equity fund tracking the NASDAQ 100 index, and a single bond fund tracking the performance of intermediate term Treasury bonds. Allocations are revised at each month-end to maximize the return while maintaining a 0.5% daily standard deviation. Table 10, Case 65 in "Conservative Computerized Investment Strategies" by Peter James Lingane, updated March 2021. Simpler versions of this strategy are described in Table 8 of this report.

Table 7. The Pinkerton Portfolio, 2000-2020. Monthly returns for the Present and Decreased Equity Allocation portfolios were generated as described in Appendix B. The allocations for the tactical strategies are variable; the values shown are averages. Different price histories were used in backtesting of the tactical strategies.

The Longevity risk of running out of money assumes 0.5% monthly withdrawals, inflation-adjusted, over twenty-five years. POR assumes 6% annual withdrawals, inflation-adjusted, over an infinite time horizon.

	Original Portfolio	**Decreased Equity Allocation**	**QQQ Dilution**	**SIMPLE RM** (Appendix C 47)	**S80**
US Equity Fund	60% VFINX	52.10%	52% QQQ	VOO	SPXL
2nd Equity Fund	15% NAESX	10.60%	None	VEU	TQQQ
Real Estate	15% FRESX	10.60% FRESX	None	XNQ	None
Bonds	5% VBMFX	13.35% VBMFX	48% IEI	IEI	TMF
2nd Bond Fund	5% VFSTX	13.35% VFSTX	None	SPTS, short Treasury bond ETF	3-mo Tbills
Rebalanced	Monthly	Monthly	Monthly	Monthly	Monthly
CAGR, per year	7.6%	7.0%	8.7%	11.1%	30.4%
mSD	4.1%	3.3%	2.5%	2.8%	8.9%
Max Drawdown	50%	42%	17%	13%	32%
Sharpe Ratio	0.48	0.51	0.84	0.98	0.97
UPI			1.46	1.99	
Annual Mean and Standard Deviation	0.0641, 0.1499	0.0550, 0.1212	0.0688, 0.0924	0.0932, 0.1069	0.3370, 0.4171
Longevity Risk @ 6% w/d over 25 years[21]	33%	34%	10%	Low	Very low
POR @ 6% w/d	61%	77%	42%	10%	4%

Source: Pinkerton Monte Carlo.xlsm, EF Performance.xlsx and Appendix B.

[21] Computed using the Monte Carlo module at portfoliovisualizer.com. See Appendix B.

The S80 tactical strategy[22] is not appropriate for the Pinkertons since this strategy is more volatile than the other strategies. It is included in Table 7 to illustrate that volatile tactical strategies can be associated with a low risk of running out of money.

Part 5. Choosing a Tactical Portfolio Strategy. This section illustrates how an investor might choose a strategy for their use.

First, the investor should choose a strategy whose monthly volatility (mSD) and bear market loss (maxDD) are consistent with the investor's temperament. If volatility and drawdowns are outside the investor's comfort zone, the investor will abandon the strategy.

In addition, the strategy must be reliable, providing better results over rolling time intervals. I compare the returns of the strategy to the returns of a 60:40 benchmark over rolling 36-month intervals (WINS36) to test for reliability.

Many successful strategies employ volatility control. In its most sophisticated rendition, this means choosing next month's portfolio allocations based on the trailing returns, volatilities and covariances of the securities in the portfolio.

I find it easiest to work with portfolios of only a few securities because this makes the monthly decisions less complicated. Returns are less spectacular than with more complex strategies, but they are attractive none the less

The QQQ Dilution strategy shown in Table 7 provides attractive statistics but the monthly calculations may challenge some investors. The performance is equally good – and easier to implement - if the monthly equity allocation is determined using a volatility-based market timing indicator. For details, see Table 8 in "Conservative Computerized Investment Strategies" at footnote 21.

The Silicon Valley Computerized Investing Group has created numerous strategies and has examined dozens of variations of dozens of strategies. Appendix C describes my approach to ranking these strategies.

[22] Allocations among SPXL (3x SPY), TQQQ (3X QQQ) and TMF (3x 20+-yr Treasury bonds) are chosen to maximize the return at 2% daily standard deviation, adding Tbills when necessary to achieve the standard deviation goal. The strategy was developed by Don Maurer. Maurer provided the equity curve from which these statistics were derived.

Conclusions

Twenty-five years of additional historical returns confirm Bengen's observation that the equity allocation does not have a strong effect on the risk of running out of money.

If the primary concern of the buy and hold investor is for their personal financial security, they should consider a portfolio with a lower equity allocation since the volatility and drawdowns will be lower. If the investor retiree has legacy ambitions, they may be willing to accept the higher volatilities associated with higher equity allocations to increase the potential value of their bequest.

Satisfactory estimates of portfolio longevity are possible with short histories by approximating the inflation-adjusted returns with a distribution.

Mortality weighting improves the accuracy of terminal values. Mortality weighting is important for long simulations of volatile strategies with high annualized returns.

A strategy which reduces volatility and drawdown is not necessarily lower risk. The best strategies are characterized by low volatility, low drawdowns and low longevity risk.

Several tactical investing strategies are identified which are "safer" than the traditional buy and hold 60:40 portfolio. These have provided volatilities similar to the traditional 60:40 portfolio and with markedly better drawdown, longevity, Sharpe and UPI characteristics. Several are easily implemented.

Investors in the fortunate position of having more resources than they need for their personal security, might consider dividing their assets into security and legacy positions and managing these positions with different strategies. The security position could be managed by one of the moderate volatility strategies identified in this Appendix while the legacy position could be targeted to more volatile strategies which provide higher returns and potentially larger bequests at death.

For Further Reading

Appendix A. Normal and Lognormal Distributions. The font in this appendix was selected to make the subscripts more legible.

When we speak of the market being up a certain percentage over a day or week or year, we are referencing the effective return. The effective return R_i equals P_i / P_{i-1} – 1, where P_i is the asset price at the end of interval i.

It is mathematically convenient to replace the effective return with the continually compounded or "log return" $r_i = \ln (P_i / P_{i-1}) = \ln (1 + R_i)$.

Alternatively, R = exp(r) -1.

Use in Historical Simulation

When computing the portfolio value at timestep T = N + 1 from the value at T = N,

$P_{N+1} = (R_{N+1} + 1) * P_{N.}$

Alternatively, $P_{N+1} = \exp(r_{N+1}) * P_{N.}$

Annualization

The effective return over a day, week or month is annualized as

$$CAGR = (P_i / P_{i-1})^\wedge(1 / N) – 1$$

where N is the length of the interval in years.

The standard deviation of the return is annualized using the Levy-Gunthorpe method. For example, the annualized standard deviation from monthly values is

$$s_a^2 = [s_m^2 + (1+m_m)^2]^{12} – (1+m_m)^{24}$$

where s_a and s_m are the annualized and monthly standard deviations and m_m is the monthly arithmetic mean.

Confirmatory Testing

1. Generate 10,000 effective returns using the EXCEL function

   NORM.INV (Rand((), m, s) where

   0 <= Rand() < 1

   m = mean (average) return = 0.050

   s = standard deviation of the returns = 0.100

   Observed mean = 0.049 – 0.051 (approximate range)

   Observed standard deviation = 0.099 – 0.101 (approximate range)

Conclusion: the observed mean and standard deviation are consistent with the assumed values.

2. If X is normally distributed, Y = exp(X) is lognormally distributed with

    mean of Y = exp(m + s^2/2)

    standard deviation of Y = SQRT(exp(2*m + s^2) * (exp(s^2) – 1))

   m and s are the mean and standard deviation of the normal distribution.

   Generate 10,000 returns equal to exp(X) where X are the normal returns from Test 1.

   Observed mean = 1.056 – 1.059 (approximate range)

   Observed standard deviation = 0.105– 0.107 (approximate range)

   Conclusion. The observed means and standard deviation of the lognormal distribution are consistent with the scaling formulas.

3. Generate 10,000 lognormal returns using the EXCEL function LOGNORM.INV (Rand(), m, s)

   0 <= Rand() < 1

   m = 0.0500

   s = 0.1000.

   The mean and standard deviation of the lognormal distribution so generated are consistent with the scaling formulas.

4. If the lognormal variable Y equals exp(X) where X is normally distributed, then ln(Y) should be normally distributed.

   Generate 10,000 returns equal to ln(X) where X are the lognormal returns from Test 3. The mean and standard deviation of the returns are consistent with M = 0.05 and s = 0.10.

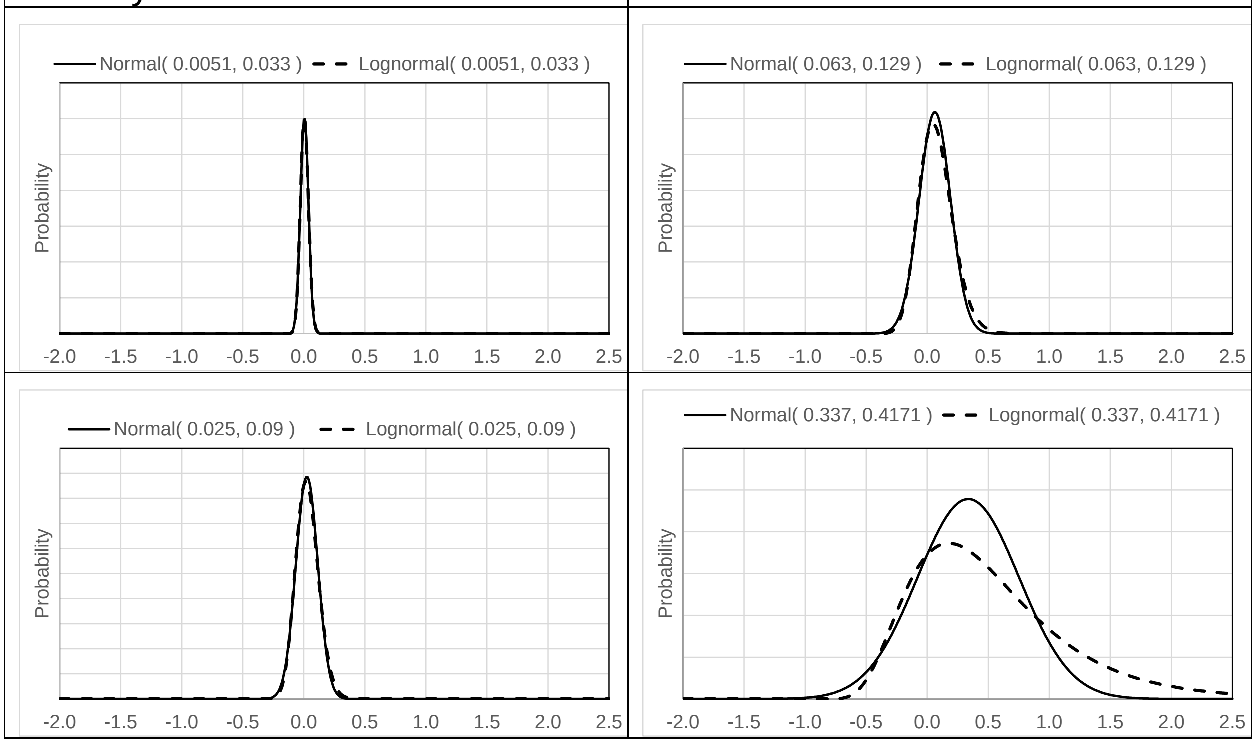
These tests confirm

- That Y = exp(X) is lognormally distributed if X is normally distributed.
- The scaling formulas between the means and standard deviations of the normal and lognormal distributions; and
- EXCEL's normal and lognormal distributions both use the mean and standard deviation of the observed returns as input.

Figure A-1. Normal and Lognormal Distributions for the 60:40 and S80 Strategies. The charts in the first row are for the 60:40 returns; the charts in the second row are for the S80 returns.

The charts plot EXCEL's NORM.DIST(X, m, SD, FALSE) vs. X and LOGNORM.DIST(1+X, m, SD, FALSE) vs. X where the values of m and SD appear in the chart legends.

Monthly Returns	Annual Returns



Source: test.xlsx

The normal and lognormal distributions of the 60:40 returns are nearly identical at both monthly and annual time scales.

Simulation of S80 using annualized returns presents challenges since some of the normal returns are less than -1, meaning that the portfolio is sometimes fully consumed in a single timestep. In addition, the differences between the normal and lognormal returns distributions are more evident at the higher standard deviation of the S80 strategy, especially at large positive returns.

Appendix B. Portfolio Visualizer Simulations

Backtest to Determine Normal Distribution Parameters

The annual mean and standard deviation shown in Table 7 are determined as follows. Default values were used for the parameters which are not mentioned.

	Present	Reconfigured
Time Period	Month to Month	
Start Year	2000	
First Month	January	
End Year	2020	
Last Month	December	
Rebalancing	Monthly	
VFINX	60%	52.10%
NAESX	15%	10.60%
FRESX	15%	10.60%
VBMFX	5%	13.35%
VFSTX	5%	13.35%

Record

Portfolio Statistics

Monthly Returns, which are not inflation-adjusted.

Annualized means and standard deviations were computed by the author from the monthly returns, after inflation adjustment, using the Levy-Gunthorpe method.

Extracting results from Portfolio Visualizer is a copy and paste operation since downloading is not a feature of a free account.

Monte Carlo Simulation to Estimate Longevity Risk

Default values were used for the parameters which are not mentioned.

	Present	Decreased Equity Allocation	QQQ Dilution	SIMPLE RM	S80
Initial Amount	1,000,000				
Cashflows	Withdraw fixed amount periodically				
Amount	5,000 per month				
Inflation Adjusted	No				
Frequency	Monthly				
Interval	30 years				
Model	Parameterized Returns				
Inflation Model	Parameterized Inflation with zero mean and zero standard deviation.				
Distribution	Normal. Expected return and volatility are inflation-adjusted.				
Expected Return	6.41	5.50	6.88	10.27	33.7
Volatility	14.99	12.12	9.24	13.50	41.7
Rebalancing	Monthly				

Record

Portfolio Balance at 25 years, 50th Percentile (median)

Portfolio Success at 25 years. The risk of failure is 1 – Success. Failure rates are shown in Table 7.

Source: Pinkerton Monte Carlo,xlsm

Appendix C. Selecting Tactical Investment Strategies of Moderate Volatility

This Appendix starts with the statistics for portfolios with fixed allocations to large cap US stocks and intermediate term bonds over the twenty-one years ending in 2020.

Portfolio	10:90	20:80	30:70	40:60	50:50	60:40	70:30	80:20	90:10	Suggested Threshold
Monthly volatility (mSD), %	0.8	0.9	1.2	1.6	2.1	2.5	3.0	3.4	3.9	3%
Bear market loss (maxDD), %	4	6	12	18	24	30	36	41	46	20%
Reliability (WINS36), %	32	32	32	32	32	100	67	67	67	60%
POR @ 5% w/d	100%	100%	99.5%	96%	90%	82%	77%	73%	70%	
POR @ 6% w/d	100%	100%	100%	99.7%	98%	94%	90%	86%	83%	20%
CAGR, %	4.8	5.1	5.4	5.7	5.9	6.1	6.2	6.3	6.4	
Sharpe	1.12	1.08	0.89	0.73	0.62	0.54	0.49	0.45	0.42	
Ulcer Performance Index	3.35	3.21	1.91	1.15	0.73	0.54	0.43	0.37	0.32	

As shown in Figure C-1, the dilemma, historically, have been between low equity allocations to reduce volatility and drawdowns and higher equity allocations to reduce longevity risk and to increase the bequest potential. Nearly four hundred tactical strategies and variations were considered[23]. There are some tactical strategies which have escaped this dilemma by reducing drawdowns and longevity risk without increasing volatility. These tactical strategies have also had better Sharpe ratios and Ulcer Performance Indices.

There are also many mediocre tactical strategies.

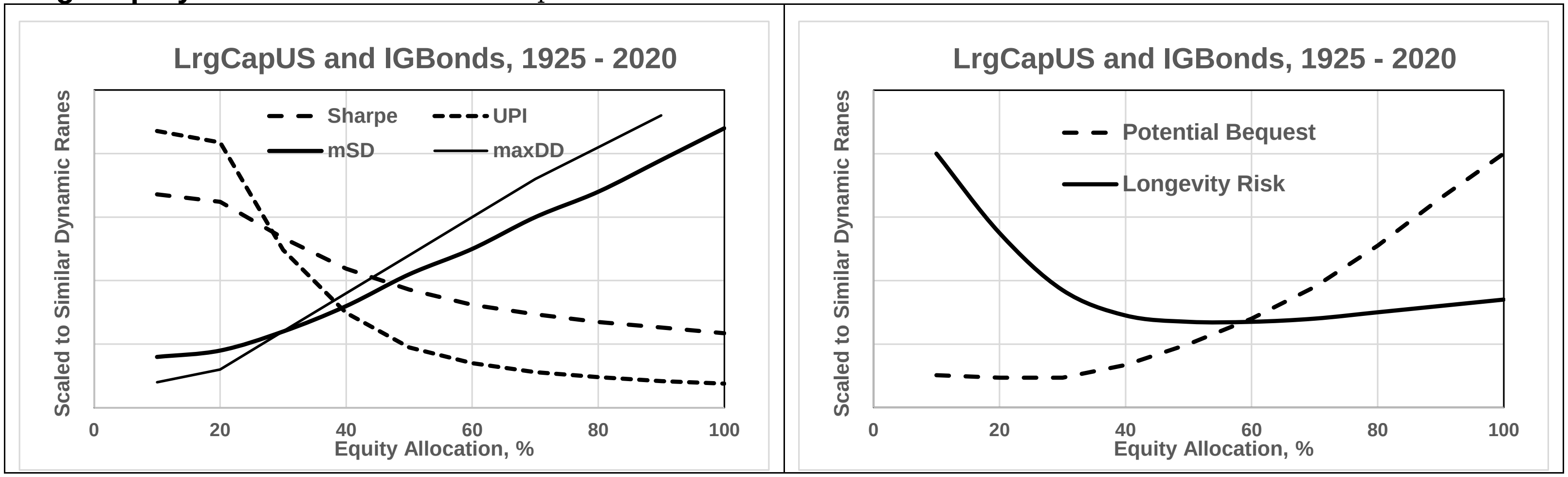
My choices for attractive statistics are anchored by my focus on my personal financial security. If your anchor is different, or if you have legacy ambitions, choose different thresholds from those shown above.

Investors in the fortunate position of having more resources than they need for their personal security might consider dividing their assets into security and legacy portfolios and managing the security and legacy portfolios with different strategies. The security position could be managed by one of the moderate volatility

[23] See the spreadsheet at www.lingane.com/qi.

strategies identified in this Appendix while the legacy position could be managed by a more volatile strategy (cite Maurer April 1 presentation) which could provide potentially larger bequests at death.

Figure C-1. One the left are the statistics which favor low equity allocations. On the right are the statistics which favor high equity allocations. Source: SequentialSimulations 01152021.xlsx.



My thresholds.

- There should be a low risk of exhausting the portfolio before death. Smaller is better. Many strategies exhibited a 20% Probability of Ruin (POR @ 6% w/d) or better over the past 21 years.
- The strategy's monthly volatility (mSD) and bear market loss (maxDD) must be consistent with the investor's temperament, or they will abandon the strategy.

  My monthly volatility threshold (mSD) is 3%, about the volatility of the 70:30 portfolio and only slightly more than the volatility of the traditional 60:40 portfolio. Many strategies exceeded this threshold.

  Maximum bear market loss (maxDD) should not exceed 20%, two thirds of the drawdown of the traditional 60:40 portfolio during the 2008 bear market.
- The strategy should provide equal or better returns than the investor's benchmark over rolling time intervals. An investor is likely to abandon a strategy which frequently provides a lower return.

My threshold is that the strategy return should exceed the return of the traditional 60:40 portfolio 80% of the time over rolling thirty-six-month intervals (WINS36). WINS36 is a challenge for many tactical strategies.

I do not set thresholds for the Sharpe ratio and UPI since strategies with good volatility, drawdown and POR characteristics tend to have good values for Sharpe and UPI. I do use the Sharpe ratio and UPI as a tiebreaker among strategies with good volatility, drawdown and POR characteristics.

No strategy scores exceedingly well on all characteristics. One must accept less than perfection.

The tactical strategies are discussed in four categories.

Section 1. Binary Portfolios of QQQ and IEI, 2000 - 2020. The QQQ allocation is controlled monthly by a timing strategy[24]. Backtested using QQQ and IGBond. Timing algorithms are based on SPX or NDX.

Timing Strategy	CAGR	Monthly SD	Sharpe	UPI	maxDD	WINS36	Annual Mean	Annual SD	POR @ 6% w/d
0.005NDX105d	0.0770	0.019	0.92	2.61	0.09	0.69	0.0573	0.0718	69%
0.005SPVolNDX	0.0802	0.019	0.98	3.05	0.07	0.74	0.0604	0.0715	60%
0.005NDX63d	0.0779	0.020	0.90	2.55	0.07	0.70	0.0584	0.0747	66%
0.006NDX105d	0.0829	0.023	0.85	1.93	0.12	0.78	0.0641	0.0861	52%
0.006SPVolNDX	0.0859	0.023	0.89	2.05	0.10	0.84	0.0670	0.0857	44%
0.006NDX63d	0.0835	0.024	0.82	1.80	0.11	0.77	0.0650	0.0899	51%
Dilution2x2to0.5%dSD	0.0827	0.025	0.84	4.14	0.16	0.81	0.0688	0.0924	42%
0.005SPVolSPX	0.0663	0.028	0.55	0.36	0.39	0.66	0.0495	0.1041	85%
0.005SPX105d	0.0655	0.029	0.53	0.42	0.35	0.67	0.0489	0.1052	86%
0.005SPX63d	0.0635	0.030	0.50	0.32	0.41	0.63	0.0473	0.1088	88%
60% VOO, 40% IEI	0.0606	0.025	0.54	0.61	0.30	reference	0.0428	0.0915	94%

One hundred twenty-three strategies for controlling the volatility of QQQ by adding IEI were considered; the ten which met the mSD threshold are shown in the table. Note the absence of StormGuard Armor.

[24] See “Definition of Timing and Allocation Algorithms” at www.lingane.com/qi.

The three strategies with relatively high drawdowns were eliminated from further consideration.

The highlighted strategies have POR values in the mid forty percent range, the lowest of the remaining seven but much higher than some other tactical strategies . Reliabilities exceed 80%. Both highlighted strategies are volatility control strategies.

Section 2. Binary Portfolios of VOO and IEI, 2000 - 2020. The VOO allocation is controlled monthly by a timing strategy. Backtested using LrgCapUS and IGBond. Timing algorithms except Armor use SPX (^GSPC).

Timing Strategy	CAGR	Monthly SD	Sharpe	UPI	maxDD	WINS36	Annual Mean	Annual SD	POR @ 6% w/d
SWAG (6-9)	0.1028	0.027	0.92	2.46	0.12	0.84	0.0851	0.1041	17%
StormGuard Armor	0.1403	0.027	1.29	5.57	0.08	1.00	0.1217	0.1052	Very low
5AbsMom	0.1026	0.028	0.90	2.24	0.14	0.81	0.0852	0.1069	18%
8mSMA	0.1071	0.028	0.93	2.31	0.15	0.84	0.0897	0.1081	13%
200dSMA + DR*VOL	0.1050	0.028	0.91	2.41	0.13	0.96	0.0876	0.1082	16%
SWAG (1-2-2-0) + DR*PR*VOL+ IUC	0.1046	0.028	0.91	2.39	0.15	0.95	0.0872	0.1080	16%
8mSMA + DR*PR*VOL + IUC	0.1036	0.028	0.90	2.41	0.15	0.95	0.0861	0.1072	17%
SWAG (6-9) + DR*PR*VOL + IUC	0.1021	0.028	0.90	2.40	0.15	0.95	0.0846	0.1062	19%
5AbsMom + DR*PR*VOL + IUC	0.1021	0.028	0.89	2.33	0.15	0.94	0.0846	0.1063	19%
5AbsMom + DR*VOL + IUC	0.0990	0.028	0.87	2.21	0.15	0.94	0.0815	0.1051	23%
5AbsMom1 + DR*PR*VOL + IUC	0.1044	0.029	0.87	2.17	0.15	0.96	0.0875	0.1123	17%
60% VOO, 40% IEI	0.0606	0.025	0.54	0.61	0.30	reference	0.0428	0.0915	94%

Timing algorithms were able to manage the volatility of binary portfolios of VOO and IEI; one hundred strategies meet the 3% mSD threshold. Many have drawdowns and longevity risks in the middle teens. The Sharpe ratio was invoked as tiebreaker at a threshold of 0.90 in choosing strategies for this table.

The unshaded strategies are composite timing strategies of long standing. Sharpe ratios are slightly less than 0.90.

Section 3 addresses the SIMPLE[25], Pinkerton, 9SPDS and 27Fido strategies.

SIMPLE strategies which allocate to the top trending fund are less attractive than SIMPLE strategies which allocate to the top two funds because they are more volatile without better statistics in other categories.

Three timed top2 SIMPLE strategies using the FundX allocation algorithm exhibit good characteristics. The statistics for the Top2 SIMPLE strategies using the FundX + Dema20 ensemble algorithm are marginally better but they are not included in the table because the ensemble algorithm is more complex.

The Top2 SIMPLE RM strategies do not use a market timing algorithm. Instead, bonds are added to the portfolio choices in the expectation that the allocation algorithm will move the portfolio to bonds in times of crisis. The three strategies shown exhibited good characteristics.

The SIMPLE RM strategies differ in their bond choices: intermediate and long Treasury bonds, intermediate and short Treasury bonds or short, intermediate and long Treasury bonds. mSD is not strongly affected by the bond choices but CAGR is improved by the presence of long bonds, with follow-on improvements to Sharpe, UPI, WINS36 and POR.

The same pattern of higher returns with long bonds holds true with the Pinkerton RM strategy.

Tactical strategies with long bonds which exhibited good characteristics in the past are likely to be low volatility strategies going forward but POR and bequest potentials are likely to be less than in the past.

The Pinkerton RM strategies are more volatile than the SIMPLE strategies.

The 9SPDR strategies timed with StormGuard Armor provided low probabilities of ruin, attractive drawdowns and volatilities which are slightly higher than the threshold. The statistics using FundX as the allocation algorithm were slightly better than using the ensemble algorithm.

The 27Fido strategies perform better with the ensemble algorithm. Some of the timed 27Fido strategies exhibit low probabilities of ruin but volatilities and maxDD are higher than with the SIMPLE strategies.

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[25] "Three Momentum Algorithms" and "Momentum Strategies to Increase Return and Decrease Risk" by Peter James Lingane, February 2017.

Section 3. The Best of the SIMPLE, Pinkerton, 9SPDR and 27Fido Strategies, 2000 - 2020. Backtested using LrgCapUS, Foreign, USREIT, SmCapUS, IGBond and VFISX. Source: SmlOutput_03202021.xlsx.

Strategy	CAGR	Monthly SD	Sharpe	UPI	maxDD	WINS36	Annual Mean	Annual SD	POR @ 6% w/d
35.SIMPLE. Top2 from among VOO, VEU & VNQ using FundX. SG Armor timing	0.1629	0.028	1.44	6.45	0.09	1.00	0.1445	0.1126	Very low
36.SIMPLE. Top2 from among VOO, VEU & VNQ using FundX. Composite timing: 5AbsMom + DR*VOL + IUC	0.1177	0.029	1.00	2.52	0.17	0.95	0.1005	0.1125	6%
37.SIMPLE. Top2 from among VOO, VEU & VNQ using FundX. Composite timing: SWAG1220 + DR*PR*VOL+ IUC	0.1230	0.029	1.04	2.78	0.17	0.94	0.1058	0.1139	4%
90.SIMPLE RM. Top2 from among VOO, VEU, VNQ, IEI & TLT using FundX.	0.1211	0.030	1.02	2.23	0.17	0.76	0.1040	0.1156	5%
S163. Same as 90.SIMPLE RM									
47.SIMPLE RM. Top2 from among VOO, VEU, VNQ, VFISX & IEI using FundX.	0.1106	0.028	0.98	1.99	0.13	0.74	0.0932	0.1069	10%
49.SIMPLE RM. Top2 from among VOO, VEU, VNQ, VFISX, IEI & TLT using FundX.	0.1147	0.029	0.98	2.03	0.17	0.74	0.0976	0.1126	8%
51.Pinkerton RM. Top2 from among VOO, DFSCX, VNQ, VFISX & IEI using FundX.	0.1133	0.034	0.85	1.64	0.17	0.77	0.0978	0.1287	13%
53.Pinkerton RM. Top2 from among VOO, DFSCX, VNQ, IEI & TLT using FundX.	0.1202	0.034	0.88	1.78	0.16	0.83	0.1052	0.1339	9%

Section 4 includes some CI Group strategies and all Allocate Smartly strategies as of March 4, 2021. Some of the better strategies from Sections 3 and 4 are included in the following table. **I hope to add more of the better Maurer strategies**

AS's Risk Premium Value Weights Proportionately to Asset Classes strategy met the mSD and POR thresholds but was eliminated because maxDD was a relatively poor 26%.

The 65% Top20DA, 35% IEI strategy may be of interest to income investors. This is a buy and hold strategy consisting of 65% of a portfolio of the Top 20 Dividend Aristocrat stocks equally weighted[26] and 35% IEI. The portfolio is rebalanced monthly. The bond allocation reduces the portfolio volatility to 2.5% per month. maxDD and POR statistics are superior to those of the 60:40 portfolio and nearly as good as for the other strategies in this table.

The Allocate Smartly strategies shown are characterized by relatively low WINS36 statistics. This suggests that the relative performance over time may not be as reliable as with other strategies. This hunch is confirmed by examining plots of relative strength over time. See Figure C-2.

Allocate Smartly assigns a trading cost of 0.1% per transaction. This has the effect of reducing the return by as much as 2.4% annually if the entire portfolio turns over each month. This trading cost seems excessive for the liquid securities used in most strategies. It has lowered the rankings of the Allocate Smartly strategies.

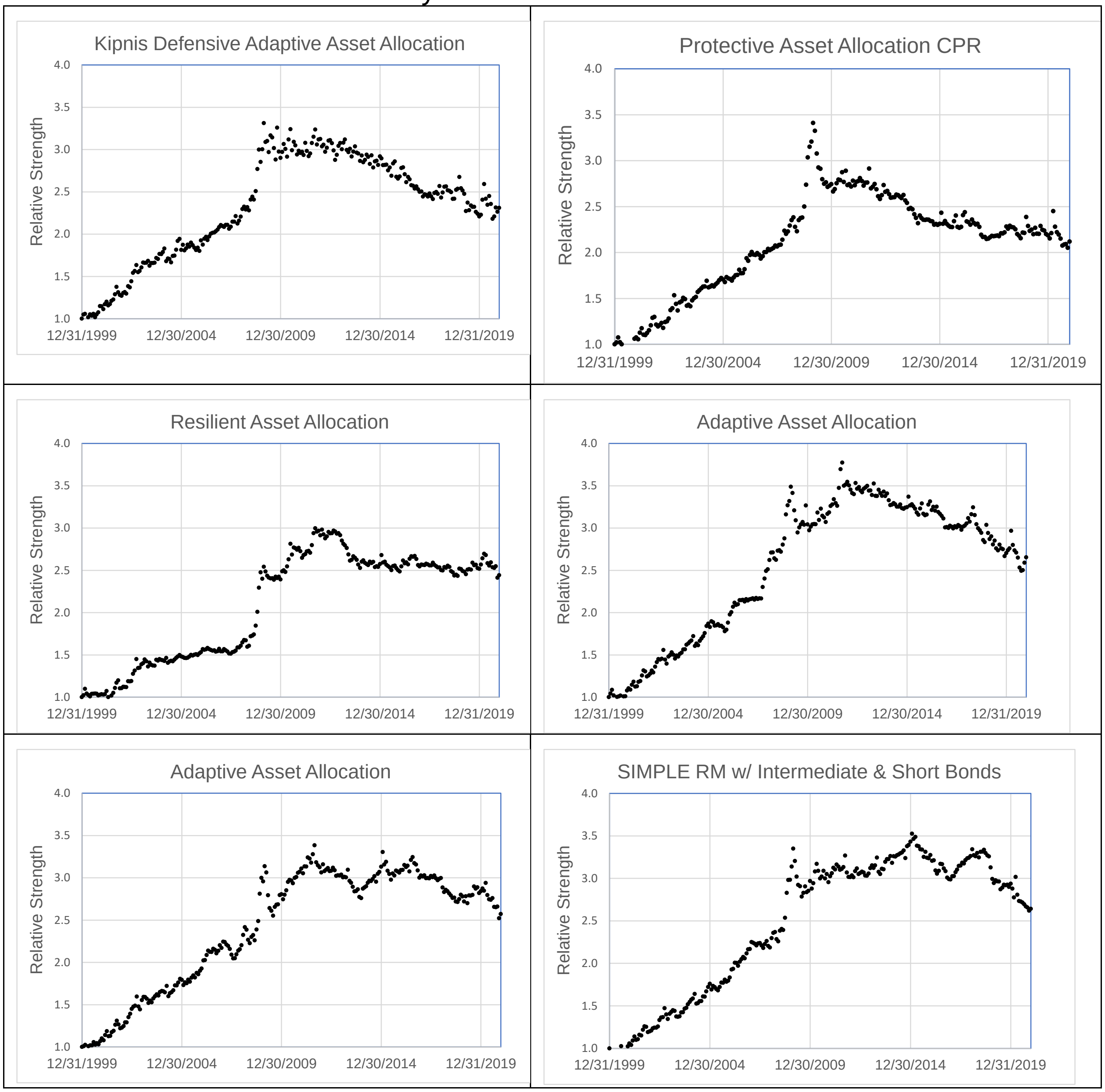
AS strategies which employ long bonds should be used with caution since long bonds will not provide the same benefits as in the past because the potential for capital gains is no longer present.

26 "Dividend Aristocrats With Longest Streak of Dividend Increases" by Derek J. Hageman, March 2011, aaii.com.

Section 4. Better CI Group and Allocate Smartly Strategies, 2000 - 2020. See www.allocatesmartly.com for the definition of the Allocate Smartly strategies. SIMPLE strategies using long bonds are excluded.

Strategy	CAGR	Monthly SD	Sharpe	UPI	maxDD	WINS36	Annual Mean	Annual SD	POR @ 6% w/d
AS Kipnis Defensive Adaptive Asset Allocation	0.1016	0.023	1.08	3.36	0.09	0.57	0.0825	0.0875	14%
AS Protective Asset Allocation	0.0992	0.023	1.06	3.54	0.07	0.53	0.0800	0.0868	17%
AS Protective Asset Allocation CPR	0.0992	0.023	1.06	3.54	0.07	0.53	0.0800	0.0868	17%
AS Resilient Asset Allocation	0.1066	0.024	1.06	3.45	0.11	0.67	0.0879	0.0950	10%
S212. Allocate among N100 true history to maximize return at 0.5% dSD. Add Tbills when necessary.	0.1018	0.025	0.98	1.26	0.20	0.81	0.0833	0.0948	16%
AS Adaptive Asset Allocation	0.1110	0.027	1.01	3.42	0.10	0.62	0.0931	0.1052	9%
SIMPLE RM. Top2 from among VOO, VEU, VNQ, IEI & VFISX using FundX.	0.1108	0.028	0.98	2.40	0.13	0.74	0.0932	0.1069	10%
AS Stoken Active Combined Asset Daily	0.1093	0.028	0.96	2.70	0.13	0.71	0.0920	0.1096	12%
AS Stoken Active Combined Asset Monthly	0.1036	0.029	0.89	2.36	0.15	0.67	0.0865	0.1113	18%
SIMPLE. Top2 of VOO, VEU & VNQ using FundX &. IEI. Market timer 5AbsMom+DR*VOL+IUC.	0.1177	0.029	1.00	2.52	0.17	0.95	0.1005	0.1125	6%
65% Top20DA, 35% IEI	0.0914	0.025	0.89	1.80	0.21	0.81	0.0731	0.0937	33%
60% VOO, 40% IEI	0.0606	0.025	0.54	0.61	0.30	reference	0.0428	0.0915	94%

Figure C-2. Relative Strength of Selected Tactical Strategies with Modest WINS36. The reference is the buy and hold 60:40 Portfolio. Source: ASStats03152021.xlsx.



Appendix D. Security Prices for Backtesting

Strategy development tends to start with the choice of the securities which will be used to implement the strategy. The securities that will be used for implementation often do not have adequate price history for backtesting. This article identifies strategies by the securities to be used in implementation. The securities used for backtesting were generally different.

Sometimes it is possible to substitute a similar fund, VFINX for SPY for example, for the needed prehistory.

Curated Data Ticker	Description	Securities Used for Backtesting	Securities Used for Implementation
"LrgCapUS" SBBI Large Company Stocks	S&P 500 plus dividends after 1956	VFINX from 1980	VOO
"IGBond" SBBI Intermediate Government Bonds	5-yr maturity Treasury bond	Equal weight blend of VFISX and VFITX 1992-2006; IEI thereafter	IEI
"Tbills" SBBI US Treasury bills	1-mo Treasury Bills	IRX 13-week index from 1998; DGS1MO 1-mo index from 2002	Money Market fund
	Short maturity Treasury bond	VFISX (1-5 year)	SPTS (1-3 year)
"LongT" SBBI Long-term Government Bonds	A "normal" bond of about 20-year maturity	TLT. Relative strength has not been compared to SBBI	VUSTX or TLT
"Inflation" SBBI Inflation	CPI-U NSA	Same	Same
"Foreign" Large Foreign Companies	MSCI-EAFA index	FSIIX 1998-2012; FSPSX thereafter	FSPSX or VEU
"USREIT" Real Estate	NAREIT	VGSIX from 1998	Same or VNQ
"SmlCapUS" SBBI small company stocks	DFA MicroCap Portfolio	DFSCX from 1986	DFSCX
NASDAQ 100 Index		QQQ price history from a quality database	QQQ
27 Fidos		Price histories are from a quality database	Fidelity Select funds
9 SPDRs		Price histories are from a quality database	SPDR sector funds

Sometimes it is possible to synthesize a reasonable prehistory based on how the security is supposed to work. The daily returns of SPXL, for example, are supposed to equal three times the daily returns of the S&P500 Composite Index with dividends. SPY is supposed to track the returns of the S&P500 Composite Index with dividends. Prehistory returns for SPXL could be constructed as three times the daily returns of SPY.

For histories that are intended to backward merge into the SBBI dataset, it is important that the relative strength of the equity curve of the security for backtesting match the equity curve from the SBBI dataset in the overlap interval. AGG is widely considered a good surrogate for intermediate term US bonds. I do not recommend AGG for backtesting or implementation because it is not a good extension for the SBBI intermediate bond price history.

Sometimes the price history is from a quality database; sometimes the price history is of uncertain quality.

Yahoo price data have frequent errors, primarily in the dividend history. The use of Yahoo data for VUSTX for backtesting strategy SIMLE RM, for example, produced the wrong allocations 8% of the time. This is understandable given Yahoo omits many the dividends.

The spreadsheet CuratedData.xlsx illustrates how Yahoo data can be cleansed.

Timing algorithms are generally based on the price and volume history of SPX, the S&P 500 Composite without dividends, or on the price of NDX, the NASDAQ 100 Composite. Basing timing algorithms on other price histories, such as that of SPY, produces different results.

The FundX allocation algorithm is the average of the 1-, 3-, 6- and 12-month total return of the securities used for backtesting.